

# The Dynamic Effects of Forward Guidance Shocks

## Technical Appendix\*

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# A Data Appendix

This appendix details how we use interest rate futures contracts to derive market-based measures of expected future interest rates. In our baseline specification in the main text, we use a Gurkaynak, Sack and Swanson (2005)-style path factor as our measure of forward guidance shocks, which is extracted from a combination of federal funds and eurodollar futures contracts. Below, we provide additional information on these futures contracts and detail how we construct our measure of forward guidance shocks.

## A.1 Federal Funds Futures Contracts

To capture unexpected changes in expectations about interest rates in the near term (one day to three months ahead), we use federal funds futures contracts. Federal funds futures contracts settle based on the average of the daily effective federal funds rate during the contract expiration month. We obtain daily data on the closing price of federal funds futures contracts from the Chicago Mercantile Exchange. Let  $p_t^j$  denote the price at time  $t$  of the federal funds futures contract expiring  $j$ -months ahead, where  $j = 0$  corresponds to the spot-month contract expiring in the current month. Then  $f_t^j = 100 - p_t^j$  is the time  $t$  expectation of the average effective federal funds rate rate  $j$ -months ahead.

### Surprise Component of the Current Target Federal Funds Rate

The day before the current FOMC meeting, the spot-month federal funds future contract satisfies:

$$f_{t-1}^0 = \frac{d_0}{m_0} r_{-1} + \frac{m_0 - d_0}{m_0} E_{t-1}(r_0) + \mu_{t-1}^0, \quad (1)$$

where  $r_{-1}$  is the annualized target federal funds rate prevailing before the meeting (which is assumed to equal the effective federal funds rate each day of the month before the meeting) and  $r_0$  is the annualized target federal funds rate after the meeting the next day. The term

$\mu_{t-1}^0$  is the term-premium for the spot-month federal funds futures contract which we assume is constant between the day before and the day of the FOMC meeting.

The next day, after the FOMC's rate decision, the spot-month federal funds future contract satisfies:

$$f_t^0 = \frac{d_0}{m_0}r_{-1} + \frac{m_0 - d_0}{m_0}r_0 + \mu_t^0. \quad (2)$$

Combining Equations 1 and 2, the unexpected policy surprise in the target federal funds rate is, denoted by  $e_t^0$ , is defined by:

$$e_t^0 \equiv r_0 - E_{t-1}(r_0) = [(f_t^0 - f_{t-1}^0) - (\mu_t^0 - \mu_{t-1}^0)] \frac{m_0}{m_0 - d_0} = (f_t^0 - f_{t-1}^0) \frac{m_0}{m_0 - d_0} \quad (3)$$

where the last equality follows from the assumption that the term-premium for the spot-month federal funds futures contract is constant between the day before and the day of the FOMC meeting. In practice, this assumption is reasonable except for meetings late in the month for which any small change in term-premia between the day-before and the day-of the FOMC meeting would be magnified by  $m_0/(m_0 - d_0)$ . To avoid this large scaling factor for events in the last week of the month, we use the following month's contract instead of the current month's contract. In this case,  $e_t^0 = f_t^1 - f_{t-1}^1$  since for meetings late in a month there is no meeting the subsequent month.

### **Surprise Component of the Funds Rate Expected After 1st-Upcoming Meeting**

While  $e_t^0$  captures the monetary policy surprise generated by changes in the current target federal funds rate, forward guidance influences expectations about the future path of the federal funds rate. Therefore, to extract policy surprises in the future path of interest rates, we assume investors know the dates of future FOMC meetings and we also extract how their expectations change for rates at the upcoming FOMC meeting. The day before the current

FOMC meeting, the federal funds future contract expiring  $i(1)$  months ahead, which is the month of the 1st-upcoming FOMC meeting, satisfies:

$$f_{t-1}^{i(1)} = \frac{d_1}{m_1} E_{t-1}(r_0) + \frac{m_1 - d_1}{m_1} E_{t-1}(r_1) + \mu_{t-1}^1, \quad (4)$$

where  $r_0$  is the annualized target federal funds rate rate set after the current meeting (which takes place the next day) and  $r_1$  is the annualized target federal funds rate rate set after the first next meeting (which takes place  $i(1)$  months in the future). The term  $\mu_{t-1}^1$  is the term-premium for the federal funds futures contract expiring  $i(1)$  months ahead, which is assumed to be constant between the day before and the day of the FOMC meeting.

The next day after the FOMC issues its statement at time  $t$ , the federal funds future contract expiring  $i(1)$  months ahead, which is the month in which the 1st-upcoming FOMC meeting takes place, satisfies:

$$f_t^{i(1)} = \frac{d_1}{m_1} E_t(r_0) + \frac{m_1 - d_1}{m_1} E_t(r_1) + \mu_t^1. \quad (5)$$

Combining Equations 4 and 5, the unexpected policy surprise in the federal funds rate expected to prevail after the 1st-upcoming FOMC meeting, denoted by  $e_t^1$ , is defined by:

$$e_t^1 \equiv E_t(r_1) - E_{t-1}(r_1) = \left[ \left( f_t^{i(1)} - f_{t-1}^{i(1)} \right) - \frac{d_1}{m_1} e_t^0 \right] \frac{m_1}{m_1 - d_1}. \quad (6)$$

For events in the last week of the month we use the next month's contract, which implies  $e_t^1 = f_t^{i(1)+1} - f_{t-1}^{i(1)+1}$ .

## A.2 Eurodollar Futures Contracts

In order to capture investors' expectations about interest rates over horizons longer than a few months, we compute the changes in eurodollar futures contracts around FOMC an-

nouncements. We obtain daily data on the closing price of USD Eurodollar futures contracts from the CME Group with contracts maturing  $i = 2, 3, 4, 5, 6, 7, 8$  quarters into the future.<sup>1</sup> Let  $r_i$  denote the annualized 3-month USD LIBOR interest rate at settlement  $i$  quarters in the future. Also, let  $p_t^{x,i}$  denote the time  $t$  closing price of the Eurodollar contract expiring  $i$  quarters in the future and  $f_t^{x,i} = 100 - p_t^{x,i}$  denote the implied rate. Then, the unexpected policy surprise, as implied by the Eurodollar contract maturing  $i$  quarters in the future, emanating from the FOMC meeting occurring on day  $t$ , is:

$$x_t^i \equiv E_t(r_i) - E_{t-1}(r_i) = f_t^{x,i} - f_{t-1}^{x,i}. \quad (7)$$

Unlike federal funds futures contracts, eurodollar futures don't settle based on the average of their underlying instrument during the settlement month. Therefore, there is no scaling necessary when using these interest rate futures contracts to extract expectations about the future path of monetary policy. For some robustness checks, we use the change in 4-, 8-, and 12-quarter ahead eurodollar futures contracts denoted by  $x_t^4$ ,  $x_t^8$ , or  $x_t^{12}$  as our measure of forward guidance shocks during the zero lower bound period.

### A.3 Computing Our Path Factor

We closely follow the appendix of Gurkaynak, Sack and Swanson (2005) to construct our path factor measure of forward guidance shocks. Their methodology uses principal component analysis to synthesize the information from numerous interest rate futures contracts into a single indicator of forward guidance surprises. We first standardize  $e^0$ ,  $e^1$ ,  $x_t^2$ ,  $x_t^3$ ,  $x_t^4$ ,  $x_t^5$ ,  $x_t^6$ ,  $x_t^7$ , and  $x_t^8$  such that each series has a mean of zero and a standard deviation of one. Then, we extract the first two principle components of these 9 time-series, denoted by  $f^1$  and  $f^2$ , over the sample of regularly scheduled FOMC meetings from January 1994 to December 2015.

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<sup>1</sup>Eurodollar futures settle in March, June, September, and December. Therefore, as an example, we define a 2-quarter ahead eurodollar future in January and February as the contract expiring in June and, beginning in March, we define the 2-quarter ahead eurodollar as the contract expiring in September.

Next, we standardize  $f^1$  and  $f^2$  and then run the ordinary least squares (OLS) regressions  $e_t^0 = \gamma_1 f_t^1 + \epsilon_t$  and  $e_t^0 = \gamma_2 f_t^2 + \epsilon_t$ . With  $\gamma_1$  and  $\gamma_2$  in hand, we transform  $f^1$  and  $f^2$  into  $z^1$  (the unscaled target factor) and  $z^2$  (the unscaled path factor) using the linear transformation:

$$\begin{bmatrix} z^1 & z^2 \end{bmatrix} = \begin{bmatrix} f^1 & f^2 \end{bmatrix} \begin{bmatrix} \alpha_1 & \beta_1 \\ \alpha_2 & \beta_2 \end{bmatrix}. \quad (8)$$

The matrix elements  $\alpha_1, \alpha_2, \beta_1, \beta_2$  are identified from the four restrictions:

**Restrictions 1 and 2:** The columns of the transforming matrix have unit length (so that the target and path factors have a standard deviation of 1).

$$\alpha_1^2 + \alpha_2^2 = 1$$

$$\beta_1^2 + \beta_2^2 = 1$$

**Restriction 3:** The target and path factors remain orthogonal after the transformation.

$$E(z^1 z^2) = \alpha_1 \beta_1 + \alpha_2 \beta_2 = 0$$

**Restriction 4:** The path factor has no influence on the current policy surprise  $e^0$ . Since,

$$f^1 = \frac{1}{\alpha_1 \beta_2 + \alpha_2 \beta_1} [\beta_2 z^1 - \alpha_2 z^2]$$

$$f^2 = \frac{1}{\alpha_1 \beta_2 + \alpha_2 \beta_1} [\alpha_1 z^2 - \beta_2 z^1],$$

then the effect of a change in  $z^2$  on  $e^0$  is defined by:

$$\frac{de^0}{dz^2} = \frac{de^0}{df^1} \frac{df^1}{dz^2} + \frac{de^0}{df^2} \frac{df^2}{dz^2} = -\gamma_1 \frac{\alpha_2}{\alpha_1 \beta_2 + \alpha_2 \beta_1} + \gamma_2 \frac{\alpha_1}{\alpha_1 \beta_2 + \alpha_2 \beta_1}$$

Hence, the restriction that  $\frac{de^0}{dz^2} = 0$  implies the parameter restriction that:  $\gamma_2 \alpha_1 = \gamma_1 \alpha_2$ .

Finally, we scale the resulting  $z^1$  and  $z^2$  vectors. We scale the target factor so that  $e_t^0$  has a one-for-one effect on it by regressing  $e_t^0 = \beta_1 z_t^1 + \epsilon_t$  and then set  $z^{target} = \beta z^1$ . We scale the path factor so that  $x^8$  has a one-for-one effect on it by regressing  $x_t^8 = \beta_2 z_t^2 + \epsilon_t$  and then set  $z^{path} = \beta_2 z^2$ .

## A.4 Comparison with Shocks From Previous Literature

In this section, we provide a detailed comparison of our path factor with some of the other forward guidance shock series from the previous literature. Table A.1 provides additional details on our methodology for constructing our path factor and provides a detailed comparison with methods of Gurkaynak, Sack and Swanson (2005), Nakamura and Steinsson (2018), Campbell et al. (2012), and Campbell et al. (2017).

Prior to the onset of the zero lower bound, we find that our path factor series behaves similar to the original Gurkaynak, Sack and Swanson (2005) path factor. Table A.2 describes the 10 largest movements in our path factor over the January 1994–November 2008 sample period and compares them with the shocks of Gurkaynak, Sack and Swanson (2005) when our sample periods overlap. Three of the four largest movements we document are included in Table 4 of Gurkaynak, Sack and Swanson (2005) despite: (i) our analysis of only scheduled FOMC meetings (they include unscheduled meetings), (ii) our use of a daily window (they use a 30-minute window), (iii) our use of longer-horizon of futures contracts (we go out to 8-quarters versus 4-quarters), (iv) and the later start and end dates of our sample (their sample is 1990–2004 whereas ours is 1994–2015). Even with these differences, for dates in Table A.2 on which we and Gurkaynak, Sack and Swanson record a shock, the signs match and, in most cases, the magnitude of the movements is similar. Moreover, we find a high correlation (0.73) between the two series during the overlapping period, which illustrates that our shock series is consistent with the seminal work in this field.

With respect to Nakamura and Steinsson (2018), we find meaningful differences between our path factor and their policy news shock series both on average and around key policy announcements. Figure A.1 below plots the two series both prior to and during the zero lower bound period.<sup>2</sup> While the two series move similarly on a small set of policy announcements, Figure A.1 shows that the quantitative fluctuations and even the sign of the shock can differ significantly both before and after the onset of the zero lower bound. As a result, the on average correlation between our path factor and the Nakamura and Steinsson (2018) policy news shock series is 0.52. Differences between the two shock series are especially visible during the zero lower bound period. While both series fall by a similar magnitude in response to the December 2008 forward guidance announcement, subsequent revisions to this guidance lead to noticeably different movements in the two series. Our path factor series declines sharply in response to the replacement of “some time” with “an extended period” in early 2009, while the Nakamura and Steinsson (2018) series only declines a bit. We also observe attenuated responses of the Nakamura and Steinsson (2018) series in response to the “mid-2013” and “late-2014” guidance. In response to the October 2010 guidance, which hinted at more future accommodation and the “mid-2015” date-based guidance, their series actually *rises* a small amount whereas our path factor series falls in both instances. These differential responses — both on average and following key changes in the FOMC’s forward guidance — likely stem from their use of a single indicator of the stance of monetary policy, which can be interpreted as an unspecified combination of changes in the federal funds rate target shocks and path factor shocks.<sup>3</sup> Given the absence of target shocks at the zero lower bound, it is also possible that their series fails to fully capture changes in the stance of policy when current policy rates are near zero.

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<sup>2</sup>We downloaded the Nakamura and Steinsson (2018) series from Emi Nakamura’s website and scaled their series to make it comparable to our path factor. Specifically, we multiplied the NS 2018 series by  $\beta$  and added  $\alpha$  to this product where:  $path_t = \alpha + \beta \times NS2018_t + u_t$  and where  $u_t$  is an OLS residual.

<sup>3</sup>In his discussion at the 2015 American Economic Association Annual Meetings, Eric Swanson also highlighted these differences relative to Gurkaynak, Sack and Swanson (2005).



Finally, we also document differences in our path factor shock relative to Campbell et al. (2012) and Campbell et al. (2017). Conceptually, Table A.1 shows that the approach in Campbell et al. (2012) is most similar to ours as they too extend the methodology in Gurkaynak, Sack and Swanson to a more recent period using daily frequency data and longer-horizon futures contracts. However, on some dates, notably on March 18, 2009, their shock series appears to differ (even in sign) from our path factor. In our experimentation, this difference is *not* reconciled by making a LIBOR adjustment to our series. Instead, it appears to be a known issue with their series, which we learned from Woodford (2012) in his Jackson Hole address (see endnote 50).<sup>4</sup> Despite these differences in our path factor series relative to some parts of the previous literature, we prefer our measure for two important reasons. First, as we discussed above, our measure produces a shock series prior to the zero lower bound which is highly correlated with the Gurkaynak, Sack and Swanson (2005) series, the seminal measure in this field. Second, during the zero lower bound, we find that changes in our shock series line up well with changes in the narrative of FOMC communication.

## A.5 Reconciling Our Results With Nakamura and Steinsson (2018)

Differences between our path factor and the Nakamura and Steinsson (2018) policy news shock series can help to reconcile our differential conclusions about the effects of forward guidance on economic activity. To illustrate this finding, we estimate two bivariate VARs. Each VAR consists of the forecasted output growth measure used in Nakamura and Steinsson

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<sup>4</sup>Campbell et al. (2012) argue that, “Markets interpreted the FOMC’s announcement as indicating that the recovery would come sooner than previously thought and that, consequently, liftoff in the federal funds rate from the ZLB would come earlier than previously anticipated; the 2-quarter-ahead futures contract rose 60 bp from the day before.” However, this assessment is at odds with our measure of Eurodollar rates on the day of this event. It is also at odds with the Federal Reserve Board staff assessment according to the April 23, 2009 Bluebook (Pg. 9): “In addition, market participants reportedly interpreted the statement that the federal funds rates was likely to remain exceptionally low for “an extended period” as stronger than the phrase “for some time” in the previous statement. Following the release of the FOMC statement, rates on Eurodollar futures contracts and yields on Treasury, agency, and mortgage-backed securities all fell considerably.”

(2018) and either our path factor or their policy news shocks measure.<sup>5</sup> Figure A.2 below illustrates the impulse responses following a shock to the Nakamura and Steinsson (2018) policy indicator (top row) or our path factor series (bottom row). In response to what should be an expansionary forward guidance shock, we initially observe a decline in forecasted output growth using their policy indicator. This initial output puzzle is consistent with the univariate regressions in Nakamura and Steinsson (2018) which suggests some robustness of their findings using a VAR framework. However, in subsequent periods, forecasted output growth increases persistently, peaking about one year after the shock. Using our path factor, we find no initial output puzzle, and instead find that expected output growth increases persistently for about two years following an expansionary forward guidance shock. These results suggest that the alternative conclusions between our work and Nakamura and Steinsson (2018) are primarily driven by differences in the shock series and the differential conclusions are not particularly influenced by the econometric methodology or measures of economic activity.<sup>6</sup>

## B Additional VAR Results

In this section, we provide additional details on our baseline empirical specification and report estimates of our empirical impulse responses with probability intervals from the robustness exercises in Figures 3, 4, & 5 in the main text.<sup>7</sup> In addition, we also present the

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<sup>5</sup>The measure of expected future output growth used in Nakamura and Steinsson (2018) is the average annualized growth rate forecasted for the current quarter, 1-quarter ahead, and 2-quarters ahead. We cumulatively sum both policy shock measures. We estimate the both empirical models over the 1995 - 2014 sample period used by Nakamura and Steinsson (2018).

<sup>6</sup>To ensure that these findings are not driven by an outsized influence of differences in the two series on a few select policy dates (such as during the zero lower bound period), we also estimate versions of these bivariate VARs controlling for dates when the two series meaningfully diverge. Specifically, we include dummy variables in the VAR for observations in which the differences between our path factor and the policy news shock series of Nakamura and Steinsson (2018) are statistically significant at the 10% level. Including these dummy variables produces similar responses to the results reported in Figure A.2, suggesting that on average differences in the two series, not simply a few outliers, help reconcile our differential conclusions with Nakamura and Steinsson (2018).

<sup>7</sup>For all probability intervals, we employ a rejection sampling approach and discard draws of the VAR parameters that imply explosive behavior. While our results regarding statistical significance of the impulse

empirical results for some additional specifications which do not appear in the main text. Our Bayesian implementation follows [Koop and Korobilis \(2010\)](#).

In our baseline VAR, we include the log levels of Macroeconomic Advisers' monthly real GDP series, its associated GDP deflator, and deflated core capital goods shipments (non-defense capital goods excluding aircraft). The capacity utilization rate and the cumulatively-summed series of monetary policy surprises are included in the VAR in levels. To proxy for real investment at a monthly frequency, we deflate core capital goods shipments by the producer price index for capital equipment. Following the conventional policy shock literature, we order our path factor series after the macroeconomic variables in our baseline specification. In addition, we also include monthly average of the 2-year constant maturity Treasury yield after our path factor as an additional control for the level of interest rates. The choice to include the 2-year Treasury yield follows from [Gertler and Karadi \(2015\)](#) and others who argue that the FOMC's forward guidance operates with roughly a two-year horizon.

## **B.1 Alternative Orderings, Indicators, & Lag Length**

Figure B.1 shows the impulse responses when we order our policy surprise series first in our recursive VAR. This ordering interprets the policy surprises as predetermined with respect to macroeconomic aggregates. Despite the fact that real economic indicators and prices are left unconstrained at impact in this specification, the probability interval of the initial response of all these variables contains zero. Moreover, when when the path factor is ordered first, the point estimates of the responses of all the variables are almost identical to our baseline VAR

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responses are generally unchanged if we rely on intervals that include these explosive draws, we find them economically uninteresting given the long-standing notion of long-run monetary neutrality. Moreover, we note that the VAR point estimates for all the models in the Appendix and the main text feature stable dynamics. If we reduce the level of significance from 90% to 68%, we find much less evidence of explosive dynamics, which suggests this issue stems from the difficulty of accurately measuring probability intervals at the 95th and 5th percentile, which is one reason why [Sims and Zha \(1999\)](#) recommend 68% posterior intervals.

model. Figure B.2 shows our findings are robust if we replace the Macroeconomic Advisers monthly GDP and GDP deflator series with industrial production and the consumer price index (CPI). Gertler and Karadi (2015) measure output and prices at a monthly frequency using these variables. These findings suggest our qualitative understanding of the effects of forward guidance shocks is not sensitive to using these alternative measures of economic activity and prices. Finally, in our baseline empirical model, the AIC for lag selection recommends the use of three lags in our VAR. However, our results are not sensitive to the inclusion of additional lags. Figure B.3 shows impulse responses to a forward guidance shock are qualitatively similar if we instead use twelve lags in our empirical specification.

## B.2 Minnesota Prior

Figure B.4 illustrates that we find similar macroeconomic effects if we use a Minnesota prior with 13 lags rather than the empirical Bayes prior we employ in our baseline specification. This prior is standard in the VAR literature and balances the need to capture the rich dynamics in the data with the concern of over-fitting the VAR by adding too many lags. The responses of real variables and prices are remarkably similar with this alternative prior. The only notable difference is the response of the 2-year Treasury yield which exhibits a more shallow decline and over-shoots by more relative to our baseline in later months. However, this quantitative difference with our baseline specification is within the range of 90% error bands for the two models.

We implement the Minnesota prior using an independent Normal-Inverse Wishart prior. Since our VAR is estimated with all variables in levels, we set the prior mean of the first own lag to one and center all of the other VAR parameters, including the intercept terms, to zero. The prior precision over the VAR intercepts is set to zero and the precision over

parameters for lag  $l$  of variable  $j$  in equation  $i$  is given by:

$$p_{i,j,l} = \begin{cases} (l/\lambda)^2, & \text{if } i = j \\ (\sigma_j^2/\sigma_i^2)(l/\lambda\theta)^2, & \text{if } i \neq j. \end{cases}$$

All off diagonal terms of the prior precision matrix are set to zero. We set  $\lambda = 0.1$  and  $\theta = 0.5$ .

In Figure B.5, we further restrict the VAR coefficients in our VAR model such that we treat the high-frequency policy surprises as exogenous shocks. In particular, we adjust the Minnesota prior so that only own lags have non-zero coefficients in the path factor equation. The dynamics of the path factor following a forward guidance shock in this alternative specification are similar to those in Figure 2 of the main text. However, the path factor and 2-year Treasury yield no longer overshoots. The responses of the macro aggregates are little changed by this restriction.

### B.3 Uninformative Priors & Alternative Forward Guidance Shocks

The estimated effects of forward guidance on real activity and prices don't meaningfully change when use uninformative priors and alternative measures of forward guidance shocks. Figure B.6 shows the impulse responses if we center the VAR parameters at the OLS estimates over the zero lower bound period rather than using an informative prior.<sup>8</sup> Using only data beyond December 2008, we observe slightly larger responses of investment, capacity utilization, and prices as well as a more persistent response of overall output. Figures B.7, B.8, and B.9 also illustrate resulting impulse responses if we measure forward guidance shocks using the changes in 4-, 8-, and 12- quarter ahead eurodollar futures rates during the zero lower bound period. Using these alternative measures of forward guidance shocks, we find largely similar responses as we found using the path factor over the post-2008 sample

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<sup>8</sup>Given the limited sample, we focus on VARs with one lag when we only use data from the zero lower bound with an uninformative prior. This decision is supported by lag-selection criteria.

period.

## **B.4 Controlling for the Possible Effects of Quantitative Easing**

Our primary empirical interest is examining the effects of a forward guidance shock at the zero lower bound. However, during the zero lower bound period, the FOMC also undertook several rounds of large-scale asset purchases. As we discuss in Section 2.6 of the main text, the announcement of many these asset purchase programs coincided with forward guidance announcements which could potentially lead to biased estimates of the effects of forward guidance. Therefore, we conduct three additional robustness checks. First, we estimate the effects of forward guidance announcements prior to the onset of the zero lower bound. Second, we drop meetings during the zero lower bound that correspond to the announcement of the asset purchase programs. Finally, we examine the effects of our forward guidance shocks on survey forecasts of future short-term interest rates. Figures B.10, B.11, and B.12 illustrate the impulse responses under these three alternative empirical specifications. As we discuss in detail in Section 2.6 of the main text, all three of these empirical specifications suggest that the presence of quantitative easing is not a key driver of our main results.

## **B.5 Calendar-Based Versus State-Based Guidance**

During the zero lower bound period, the FOMC relied on calendar-based guidance (“extended period”), date-based guidance (“mid-2013”), and state-dependent guidance (inflation and unemployment rate thresholds). Separately decomposing the effects between calendar, date-based, and state-dependent guidance likely requires more observations of each type than we have available at this time. However, we note that most of the guidance from the FOMC at the zero lower bound was calendar/date-based, except for a brief turn towards threshold-based or state-dependent guidance from December 2012 to January 2014. Therefore, we can attempt to estimate the effects of calendar/date-based guidance by estimating our VAR from

December 2008 through November 2012 – just prior to the temporary switch to state-based guidance. Figure B.13 below shows that the estimated responses using this earlier sample period are qualitatively similar to the full sample estimates. The most noticeable differences are the shape of the output response, which rises sharply and more quickly following the forward guidance shock, and the response of investment, which exhibits an initial decline before rising in later periods. However, this investment response doesn't appear to be statistically different from our baseline estimates after accounting for the uncertainty around both investment responses.

## B.6 Risk-Premia in Interest Rate Futures

We make no explicit risk-premium adjustment to the federal funds futures nor eurodollar futures when constructing our forward guidance surprises. This approach is supported by the analysis in Piazzesi and Swanson (2008). They show that there is a low-frequency risk-premium in federal funds and eurodollar futures that varies across the business cycle (month-to-month). However, they find that the one-day change in futures around FOMC meetings – as we use – is more robust to the presence of time-varying risk premium in these contracts. They hypothesize that, “The difference-based measure may largely ‘difference out’ risk premia that are moving primarily at lower, business-cycle frequencies ...” For example, they can't reject the null of no contamination by time-varying risk premia for the Kuttner (2001)-type daily-frequency shocks.

However, we use eurodollar futures extending 2 years ahead (and even 3 years ahead in some robustness checks). This horizon is well beyond what Piazzesi and Swanson (2008) consider.<sup>9</sup> Therefore, we use survey forecasts of short-term interest rates to quantify the role

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<sup>9</sup>In results available upon request, we repeat the exercise in Piazzesi and Swanson (2008) for our forward guidance shock measures and test whether Treasury yields the day before the FOMC announcement have any predictive content for high-frequency policy surprises. The results of these predictive regressions reveal that we cannot reject the null of no contamination by time-varying risk premia for our path factor. For the

that time-varying risk or liquidity premia might play in shaping our results. In particular, we add the Blue Chip consensus forecast of the short-term interest rate 4-quarters ahead to our VAR and order it last in place of the 2-year Treasury yield. In this specification, we use the 4-quarter ahead eurodollar future to measure the high-frequency forward guidance surprise and estimate the VAR during the zero lower bound period with an uninformative prior. If our financial market-based forward guidance shocks embody time-varying risk (or liquidity) premia in the futures rates, then we would expect significant differences between the response of survey forecasts of rates 4-quarters ahead and 4-quarter ahead eurodollar rates reflecting these premia. However, after accounting for uncertainty surrounding the estimated responses, Figure B.14 suggests that it would be difficult to reject the hypothesis that the response of the 4-quarter eurodollar rate coincides with the response of the 4-quarter ahead forecasts of short-term rates from Blue Chip. This could result from the fact that (1) the lagged macroeconomic variables included in our VAR effectively cleanse any risk premia that vary at the business-cycle frequency from our forward guidance shock measures or (2) our high-frequency daily change in federal funds and eurodollar rates may, in the words of Piazzesi and Swanson, “difference-out” any low-frequency risk premia.

## **B.7 Comparison to Gertler and Karadi’s Proxy-VAR Approach**

Our empirical strategy essentially treats high-frequency surprises as an “internal instrument” by including the cumulative sum of these surprises as an endogenous variable inside the VAR. However, in an important paper, Gertler and Karadi (2015) use high-frequency monetary policy surprises as an external instrument to identify monetary policy shocks. Given the potential for these two approaches to lead to different conclusions regarding the effects of forward guidance, we compare the impulse responses under these two econometric strategies. Therefore, we originally attempted to use our path factor series as an external 

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individual eurodollar surprises, we also find no evidence that they are contaminated by risk premiums.



instrument using the 2-year Treasury yield as the monetary policy indicator in our baseline VAR model. However, just as Gertler and Karadi (2015, pg. 69) report, we too found that “this decomposition between target and path factors leads to instruments that are too weak in the context of our external instruments setup to credibly identify pure surprises to forward guidance.”<sup>10</sup> We found similar first-stage results using our path factor as an external instrument in Gertler and Karadi’s smaller VAR, which consists of the natural log of industrial production, the natural log of the consumer prices index, the 2-year constant maturity Treasury yield, and the excess bond premium from Gilchrist and Zakrajšek (2012).

In light of the fact that we too found that the path factor is a very weak first-stage instrument, we took the following approach to compare our empirical strategy to the Gertler and Karadi (2015) proxy VAR approach. First, we estimated Gertler and Karadi’s VAR model using their “conceptually preferred policy indicator/ instrument variables combination” of forward guidance shocks. In particular, in Figure 8 of their paper, they report results using the 2-year constant maturity Treasury yield as the policy indicator and the full set of GSS instruments (not the path factor principle component, but rather all the underlying futures rates). We downloaded their data from the AEA’s website and estimated their proxy VAR model using data only over the January 1994 to June 2012 sample, the period for which the their data overlaps with ours. We included three lags of the endogenous variables as suggested by lag selection criteria.<sup>11</sup> The impulse responses from this model are shown by the solid blue lines in Figure B.15.<sup>12</sup> Next, we estimated a five variable VAR which includes the four variables in the Gertler and Karadi model and adds the cumulative sum of our path

---

<sup>10</sup>In particular, the first-stage F-statistic is nearly zero.

<sup>11</sup>We used the code of Ambrogio Cesa Bianchi to calculate the Gertler and Karadi impulse responses and confidence bands, downloaded from <https://sites.google.com/site/ambropo/MatlabCodes> since Gertler and Karadi’s MATLAB code on the AEA website requires the econometrics toolbox.

<sup>12</sup>Over this sample, our estimates are similar, albeit a bit stronger compared to those reported in Gertler and Karadi (2015) who estimate the VAR lag coefficients and obtain the reduced form residuals over the 1979-2012 sample and then estimate the first-stage IV regressions from 1991-2012. We might speculate the stronger responses are emanating from the fact that policy statements weren’t issued until 1994 which likely led to greater variation in forward guidance over this post-1994 sample.

factor series, ordered first. We estimated this model over the same January 1994 to June 2012 sample using the same number of lags (three). The impulse responses from the two approaches are scaled to generate the same (cumulative) movement in the 2-year Treasury yield over the 48 periods of the impulse response. The impulse responses from this model are shown by the dashed red lines in Figure B.15.

Figure B.15 shows that the two estimation strategies produce similar impulse responses. In particular, both sets of impulse responses show that 2-year Treasury rates decline on impact and remain low for the first year, reflecting the expansionary forward guidance. This forward guidance shock results in easier financial conditions as the excess bond premium persistently declines for one to two years. Output rises in a hump-shaped pattern and the rise in output persists well beyond the time that Treasury rates return to their pre-shock levels. This expansion results in inflationary pressures, as prices rise for the next several years. Quantitatively, the two approaches yield similar conclusions regarding the effects of forward guidance. For all variables, the point estimate from our estimation strategy reside in the confidence bands from the Gertler and Karadi (2015) proxy VAR approach for much of the impulse response horizon. Focusing especially on the response of output, which is the central to the forward guidance puzzle, the output response from our estimation strategy (the dashed red line) resides in Gertler and Karadi’s confidence intervals for the entire impulse response horizon. The comparison affirms that, at least for the overlapping January 1994 to June 2012 sample, the proxy VAR model of Gertler and Karadi and our approach produce similar output effects following a forward guidance shock.

## **B.8 Response of TIPS Yields to Forward Guidance Shock**

Nakamura and Steinsson (2018), building on the work of Campbell et al. (2012), argue that, in addition to providing news about future interest rates (an Odyssean component),

monetary policy announcements contain a significant amount of macroeconomic news (a Delphic component). If the Delphic component dominates, then an unexpected decline in policy rates could *lower* forecasts of economic activity. Our estimates of the effects of forward guidance should be interpreted as an on-average, net-effect of FOMC communication. The VAR evidence we find seems to suggest that, among these two channels, the Odyssean effect dominates, on average. While there may be Delphic components to some FOMC announcements, we find that those influences are typically more than offset by expansionary Odyssean effects. To illustrate this idea, Figure B.16 shows the impulse responses if we include the five-year inflation-protected Treasury yield in our VAR model, a key variable of interest in Nakamura and Steinsson (2018). These authors argue that a lower path of the policy rate signals a lower natural real rate of interest, which causes long-term real interest rates to fall and lowers expectations for output growth. In contrast, we find that forward guidance shocks lower financial market measures of long-term real interest rates and *raise* actual output, which is consistent with the predictions of a standard model of monetary policy without a macroeconomic news channel.

## C Model

In the symmetric equilibrium, the baseline model in Dynare notation is as follows:

```
model;
```

```
// Private Sector
```

```
y = pd^(-1)*n^(1 - alpha)*(u*k(-1))^alpha;
```

```
y = c + inv;
```

```
w = chi*(a/lambda)*n^eta;
```

```
lambda = a * (c - b*c(-1))^(1-alpha);
```

```
1 = beta * (lambda(+1)/lambda) * ( r/pie(+1) );
```

```
1 = beta * (lambda(+1)/lambda) * ( rr );
```

```
w = (1 - alpha)*(y*pd/n)/mu;
```

```
rrk*u = alpha*(y*pd/k(-1))/mu;
```

```
q*deltauprime*k(-1) = alpha*(y*pd/u)/mu;
```

```
k = (1 - deltau)*k(-1) + inv*( 1 - (phii/2)*(inv/inv(-1)-1)^(2) );
```

```
deltau = delta0 + delta1*(u-1) + (delta2/2)*(u-1)^(2);
```

```
deltauprime = delta1 + delta2*(u-1);
```

```
g1 = lambda*y/mu +
```

```
omega*beta*(pie(+1)/(piess^(1-gamma)*pie^gamma))^(theta)*g1(+1);
```

```
g2 = piestar*(lambda*y + omega*beta*((pie(+1)/(piess^(1-gamma)*pie^gamma))^(theta-1)  
/piestar(+1))*g2(+1));
```

```

1 = omega*(pie/(piess^(1-gamma)*pie(-1)^gamma))^(theta-1)
+ (1-omega)*(piestar^(1-theta));
pd = omega*(pie/(piess^(1-gamma)*pie(-1)^gamma))^(theta)*pd(-1)
+ (1-omega)*piestar^(-theta);

theta*g1 = (theta-1)*psi*g2;

1 - q*(1 - (phii/2)*(inv/inv(-1)-1)^(2) - phii*(inv/inv(-1)-1)*(inv/inv(-1)) )
= beta * q(+1) * (lambda(+1)/lambda) * phii * (inv(+1)/inv - 1)*(inv(+1)/inv)^(2);
q = beta * (lambda(+1)/lambda) * ( rrk(+1)*u(+1) + q(+1) * (1 - deltau(+1)) );

a = (1-rhoa)*ass + rhoa * a(-1) + vola*ea;
nu = rhonu * nu(-1) + volnu*enu;

// Lagged Expectations

expy1 = y(+1);
lagey = expy1(-1);
expinv1 = inv(+1);
lageinv = expinv1(-1);
expu1 = u(+1);
lageu = expu1(-1);
exppie1 = pie(+1);
lagepie = exppie1(-1);

// Monetary Policy Rule

```

```

log(rd) = phir*log(rd(-1)) +
(1-phir) * (log(rss) + phipie*log(pie/piess) + phix*log(y/yss)) + nu;
r = rd;

```

```
// Eurodollar Futures Rates
```

```

expr1auxiliary = r(+1);
expr2auxiliary = expr1auxiliary(+1);

```

```

1 = ( 1 - 12*(1/3)*(log(r(+1)) +
log(expr1auxiliary(+1)) + log(expr2auxiliary(+1)) ) ) / edf1;

```

```
1 = edf1(+1) / edf2;
```

```
1 = edf2(+1) / edf3;
```

```
1 = edf3(+1) / edf4;
```

```
1 = edf4(+1) / edf5;
```

```
1 = edf5(+1) / edf6;
```

```
1 = edf6(+1) / edf7;
```

```
1 = edf7(+1) / edf8;
```

```
1 = edf8(+1) / edf9;
```

```
1 = edf9(+1) / edf10;
```

```
1 = edf10(+1) / edf11;
```

```
1 = edf11(+1) / edf12;
```

```
1 = edf12(+1) / edf13;
```

```
1 = edf13(+1) / edf14;
```

```
1 = edf14(+1) / edf15;  
1 = edf15(+1) / edf16;  
1 = edf16(+1) / edf17;  
1 = edf17(+1) / edf18;  
1 = edf18(+1) / edf19;  
1 = edf19(+1) / edf20;  
1 = edf20(+1) / edf21;  
1 = edf21(+1) / edf22;  
1 = edf22(+1) / edf23;  
1 = edf23(+1) / edf24;
```

```
expr1edf = 1 - edf1;  
expr2edf = 1 - edf2;  
expr3edf = 1 - edf3;  
expr4edf = 1 - edf4;  
expr5edf = 1 - edf5;  
expr6edf = 1 - edf6;  
expr7edf = 1 - edf7;  
expr8edf = 1 - edf8;  
expr9edf = 1 - edf9;  
expr10edf = 1 - edf10;  
expr11edf = 1 - edf11;  
expr12edf = 1 - edf12;  
expr13edf = 1 - edf13;  
expr14edf = 1 - edf14;  
expr15edf = 1 - edf15;
```

```
expr16edf = 1 - edf16;  
expr17edf = 1 - edf17;  
expr18edf = 1 - edf18;  
expr19edf = 1 - edf19;  
expr20edf = 1 - edf20;  
expr21edf = 1 - edf21;  
expr22edf = 1 - edf22;  
expr23edf = 1 - edf23;  
expr24edf = 1 - edf24;
```

```
// Bond Prices & Yields
```

```
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * (1) / bp1;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp1(+1) / bp2;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp2(+1) / bp3;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp3(+1) / bp4;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp4(+1) / bp5;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp5(+1) / bp6;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp6(+1) / bp7;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp7(+1) / bp8;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp8(+1) / bp9;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp9(+1) / bp10;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp10(+1) / bp11;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp11(+1) / bp12;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp12(+1) / bp13;  
1 = beta * (lambda(+1)/lambda) * (1 / pie(+1)) * bp13(+1) / bp14;
```



$1 = \beta * (\lambda(+1)/\lambda) * (1 / \pi(+1)) * bp14(+1) / bp15;$   
 $1 = \beta * (\lambda(+1)/\lambda) * (1 / \pi(+1)) * bp15(+1) / bp16;$   
 $1 = \beta * (\lambda(+1)/\lambda) * (1 / \pi(+1)) * bp16(+1) / bp17;$   
 $1 = \beta * (\lambda(+1)/\lambda) * (1 / \pi(+1)) * bp17(+1) / bp18;$   
 $1 = \beta * (\lambda(+1)/\lambda) * (1 / \pi(+1)) * bp18(+1) / bp19;$   
 $1 = \beta * (\lambda(+1)/\lambda) * (1 / \pi(+1)) * bp19(+1) / bp20;$   
 $1 = \beta * (\lambda(+1)/\lambda) * (1 / \pi(+1)) * bp20(+1) / bp21;$   
 $1 = \beta * (\lambda(+1)/\lambda) * (1 / \pi(+1)) * bp21(+1) / bp22;$   
 $1 = \beta * (\lambda(+1)/\lambda) * (1 / \pi(+1)) * bp22(+1) / bp23;$   
 $1 = \beta * (\lambda(+1)/\lambda) * (1 / \pi(+1)) * bp23(+1) / bp24;$

$ytm1 = -(1/1)*\log(bp1);$   
 $ytm2 = -(1/2)*\log(bp2);$   
 $ytm3 = -(1/3)*\log(bp3);$   
 $ytm4 = -(1/4)*\log(bp4);$   
 $ytm5 = -(1/5)*\log(bp5);$   
 $ytm6 = -(1/6)*\log(bp6);$   
 $ytm7 = -(1/7)*\log(bp7);$   
 $ytm8 = -(1/8)*\log(bp8);$   
 $ytm9 = -(1/9)*\log(bp9);$   
 $ytm10 = -(1/10)*\log(bp10);$   
 $ytm11 = -(1/11)*\log(bp11);$   
 $ytm12 = -(1/12)*\log(bp12);$   
 $ytm13 = -(1/13)*\log(bp13);$   
 $ytm14 = -(1/14)*\log(bp14);$   
 $ytm15 = -(1/15)*\log(bp15);$

```
ytm16 = -(1/16)*log(bp16);  
ytm17 = -(1/17)*log(bp17);  
ytm18 = -(1/18)*log(bp18);  
ytm19 = -(1/19)*log(bp19);  
ytm20 = -(1/20)*log(bp20);  
ytm21 = -(1/21)*log(bp21);  
ytm22 = -(1/22)*log(bp22);  
ytm23 = -(1/23)*log(bp23);  
ytm24 = -(1/24)*log(bp24);  
  
end;
```

Since the capital stock is predetermined, we lag the capital stock  $K$  variables by one period relative to the timing in the model derivation.

## C.1 Estimation Strategy

Using a Bayesian impulse response matching estimator, we estimate several model parameters by finding the values which maximize the posterior distribution. Let  $\hat{\psi}$  denote the impulse response functions for the 6 variables in our empirical VAR stacked into a single vector with  $(6 \times 48 = 288)$  rows and let the diagonal matrix  $V^{-1}$  denote a measure of the precision of the empirical impulse responses.<sup>13</sup> Then, let  $\psi(\gamma)$  denote the theoretical model's corresponding counterpart to  $\hat{\psi}$ . Following Christiano, Trabandt and Walentin (2010), we can write the approximate likelihood function as follows:

$$L(\hat{\psi} \mid \gamma, V) = (2\pi)^{-\frac{N}{2}} |V|^{-\frac{1}{2}} \exp \left[ -0.5(\hat{\psi} - \psi(\gamma))' V^{-1} (\hat{\psi} - \psi(\gamma)) \right].$$

Let  $p(\gamma)$  denote the joint prior density over  $\gamma$ . According to Bayes rule,

$$f(\gamma \mid \hat{\psi}, V) \propto L(\hat{\psi} \mid \gamma, V) p(\gamma), \quad (9)$$

where  $f(\gamma \mid \hat{\psi}, V)$  is the posterior density over  $\gamma$ . Our estimator solves the following problem:

$$\max_{\gamma} f(\gamma \mid \hat{\psi}, V). \quad (10)$$

Christiano, Eichenbaum and Trabandt (2016) provide three reasons why this is only an approximate likelihood: (i) Standard asymptotic theory implies that under the assumption that the DSGE model is the correct data generating process with the true parameters  $\gamma_0$ ,  $\hat{\psi}$  converges only asymptotically to  $N(\psi(\gamma_0), V)$  as the sample size grows arbitrarily large, (ii) our proxy for  $V$  is guaranteed to be correct only as the sample size grows arbitrarily large, and (iii)  $\psi(\gamma)$  is approximated with a piece-wise linear DSGE model. A referee brought to

---

<sup>13</sup>The diagonal of  $V^{-1}$  contains one over the squared difference between the 95th and 5th percentile of the empirical probability interval. Omitting off-diagonal terms from  $V$  helps make our estimator more transparent as it attempts to place the model's impulse responses inside the empirical probability intervals.

our attention a fourth reason in our application: (iv) in a non-linear model, the IRFs are not a full summary of the model like they are in a linear model.

## D Additional Model Results

### D.1 Comparing Our Specification with News-Shocks Approach

The forward guidance shock specification we use in our model differs from the work of Del Negro, Giannoni and Patterson (2015) and Keen, Richter and Throckmorton (2015), which use anticipated “news” shocks about future monetary policy to model forward guidance shocks. In this section, we show that we can achieve nearly identical macroeconomic effects from either our specification or a news-shock approach. For this exercise only, we replace our monetary policy rule in Equations (2) - (4) of the main text with the following specification:

$$r_t^d = \phi_r r_{t-1} + (1 - \phi_r) \left( r + \phi_\pi (\pi_t - \pi) + \phi_y y_t \right) + \sum_{s=0}^N \sigma^\nu \varepsilon_{t-s}^s \quad (11)$$

$$r_t = \max(0, r_t^d) \quad (12)$$

where  $r_t^d$  is the desired policy rate of the monetary authority,  $r_t$  is the actual policy rate subject to the zero lower bound, and the final summation term captures the effects of  $N$  different horizon “news” shocks about monetary policy.  $\varepsilon_{t-s}^s$  is a “news” shock about future monetary policy that agents learn about in period  $t - s$  but then becomes realized in period  $t$ . For example,  $\varepsilon_{t-2}^2$  is an exogenous shock to the level of policy rates today that agents learned about in period  $t - 2$ . We assume all of the news shocks are independent and identically-distributed normal random variables. Relative to our baseline specification, this news-shock approach replaces the smoothing in the desired policy rate with the actual policy rate and incorporates a variety of news shocks rather than our previous autocorrelated shock

$\nu_t$ .

Conditional on generating the same path of nominal interest rates, our baseline specification and this alternative news shock approach generate nearly identical macroeconomic effects. To illustrate this idea, we first use an estimated quarterly-frequency version of our baseline model to generate two paths for interest rates. In the first time path, we simulate a large negative demand shock which causes the zero lower bound to bind for seven quarters. In the second time path, we simulate the same large negative first moment demand shock but also simulate a negative shock to the desired policy rate in Equation (4). Using these two paths of interest rates from our baseline model, we then solve for two sequences of news shocks  $\varepsilon_{t-s}^s$  for  $s = 0, 1, \dots, N$  such that the news shock economy generates the same two paths of interest rates as the desired rate economy. We then compute the impulse response in the news shock economy by taking the difference between the key variables of interest under these two different paths of interest rates. Figure D.1 illustrates that our baseline specification and the news-shock approach generate similar macroeconomic outcomes, which shows that our desired rate approach to modeling forward guidance shocks is not strictly necessary to generate our main results.

Intuitively, we think of our specification of monetary policy, which uses shocks to the desired policy rate, as quite similar to the “news” shock approach from other papers in the literature. However, implementing the news-shock approach suffers from three significant drawbacks, which we outline below:

1. Simulating an  $n$ -period ahead news shocks adds  $n$  additional state variables to model (the news shock itself plus  $n - 1$  auxiliary variables to properly model the agent’s information set).
2. The news-shock approach typically needs many news shocks in order to produce a

data-consistent path of interest rates in response to a forward guidance shock. In the data, a forward guidance shock almost always moves futures rates across all horizons in the same direction. For example, 1, 2, & 3-year ahead futures rates all fell following the August 2011 FOMC announcement. However, matching this feature of the data using a news-shock approach can be quite challenging.

As an example, consider a 24-month ahead news shock that lowers two-year ahead expected policy rates. Agents learn about that shock today, which causes an output and prices to increase through the forward-looking decision of households and firms. Since the central bank sets its policy rate as a function of output and inflation, policy rates both today and over the next several periods *increase* even though the forward guidance shock will lower policy rates in the two years. Thus, futures rates with less than two years to maturity would also rise while futures rates with two-year or greater horizon would fall, which is inconsistent with the data and the typical type of policy experiments that we think are of interest to policymakers.

To correct this issue, we need to simulate additional news shocks to prevent short-term rates from rising in response to an expansionary forward guidance shock. This issue explains why we need to include many different horizon news shocks in our news shock specification. Returning to the example from the previous paragraph, we can use a sequence of expansionary news shocks in periods 1-23 to generate a path of interest rates that doesn't rise following the announcement of an expansionary news shock in period 24. Depending on the exact numerical exercise, however, one news shock for each horizon of the impulse response may be required to generate the needed path for interest and futures rates. Given that each  $n$ -horizon news shock adds  $n$  state variables, the number of state variables can easily become quite large. For example,

in our baseline monthly-frequency model, adding 48 news shocks (the length of our impulse responses) would add 1176 state variables to model, which makes it quite time consuming to solve and simulate the model for a fixed set of parameters and would make estimation of the model infeasible.

3. Beyond the size of the state space necessary to implement the news-shock approach, solving for the sequence of news shocks to match a path of interest rates remains a difficult computational problem. Since two different sequences of news shocks may produce similar paths of interest rates, numerical optimizers tend to have difficulty jointly identifying the correct sequence of shocks. We find that an iterative approach, solving for each news shock individually and looping over different horizons, tends to be a more robust solution method but it still takes quite a bit of time to solve for the entire sequence of shocks. In addition, we find that choosing the correct starting horizon for the algorithm is crucially important, which tends to differ across parameterizations or numerical exercises. This need for human input from the modeler and the required computational time crucially rules out our ability to estimate the model under the news-shock approach.

Given these three key drawbacks, we prefer our desired rate specification for simulating a forward guidance shock. However, we note that the “economics” of this state variable issues we discuss in (1) and (2) above slightly improve under a quarterly-frequency model. Thus, we estimate a quarterly-frequency version of our model (which limits the maximum number of news shocks  $N = 16$ ) in this section to show the equivalence between our specification and the news-shock approach. However, changing the frequency of the model does not fully solve the computational issues involved with solving for the necessary sequence of forward guidance shocks. Overall, we think our desired rate specification is a very tractable way to

simulate forward guidance shocks at the zero lower bound.

## D.2 Model-Based Support for Empirical Identification

In our empirical analysis, we use a standard linear VAR to trace out the dynamic effects of a forward guidance shock. However, this approach is subject to two critiques. First, can our empirical model actually recover the true structural forward guidance shocks of interest? Second, since the zero lower bound introduces a significant non-linearity in the economy, can a standard linear VAR adequately capture the responses to a forward guidance shock at the zero lower bound? In this section, we estimate our empirical specification on simulated data from our theoretical model to examine these two issues. Overall, we find that our empirical specification performs well at recovering the true structural shocks and impulse responses when our theoretical model is the true data generating process.

We follow the procedure in De Michelis and Iacoviello (2016) to estimate our empirical specification on artificial data at the zero lower bound. First, we simulate our theoretical model for 15 years using a sequence of preference and forward guidance shocks. For the forward guidance shocks, we draw a sequence of random shocks for  $\varepsilon_t^v$  in Equation (3) of the main text. For the sequence of preference (aggregate demand) shocks, we simulate a constant, negative sequence of shocks that will take the economy goes to the zero lower bound for a very long period of time. Solving the model using this sequence of shocks produces a simulated series for output, investment, capacity utilization, prices, and 24-month futures rates.<sup>14</sup>

We then run our empirical specification on this artificial data. We repeat this exercise 1000

---

<sup>14</sup>Since our model is recursive, we use the lagged expectations of the macro variables in the VAR when conducting this exercise to be consistent with the timing assumptions in the model. To be consistent with our high-frequency identification strategy in the data, which only examines the effects of forward guidance shocks around policy announcements, we take the difference between the futures rates that occurred after the forward guidance shock and the futures rates that would have prevailed without the forward guidance shock. As in our empirical specification, we then take the cumulative sum of those changes each period and input that resulting series into the VAR.



times and examine the estimated shocks and impulse responses and compare them with their true model counterparts.

We find that our empirical specification performs well at recovering the true structural shocks and impulse responses. Even in a small sample, we find that the correlation between the true and our estimated shocks is quite high (above 0.85). Moreover, Figure D.2 shows that our empirical framework generally performs adequately in recovering the true impulse responses. The true response of output from our structural model falls within the 90% probability band of our simulation exercise, suggesting that an econometrician would likely uncover the true model-implied response of output. While the estimated responses for investment, capacity utilization, and the price level are a bit smaller than the true responses, the estimated effects are qualitatively consistent with the structural responses. For the path of the 24-month futures rate, we find that our empirical method implies a slightly smaller but more persistent response of futures rates relative to the true response. Taken together, however, these results suggest that our empirical method would be generally successful at uncovering the correct forward guidance shocks and their macroeconomic effects in the data.

## **E Additional Impulse Response Matching Results**

This section presents additional results from our impulse response function (IRF) matching procedure we use to estimate the model parameters.

### **E.1 Output Growth in Policy Rule**

In our estimation, the feedback coefficients on the monetary policy rule to inflation and the output gap are calibrated to the values suggested by Taylor (1993). But, other variants of Taylor rules have been shown to fit the data better, particularly by including a response to output growth. Therefore, we carried out a robustness check in which we replaced the output

gap reaction with an output growth reaction in the central bank’s policy rule. Figure E.1 below shows the resulting estimated model impulse responses under an output growth rule and the original output gap rule.<sup>15</sup> We find that the model fits the empirical VAR estimates similarly well using either an output gap or output growth rule.

## E.2 Small-Scale Model without Capital

Our baseline model mirrors many of the features of the model in Christiano, Eichenbaum and Evans (2005) by including investment, investment adjustment costs, and variable capital utilization. However, simpler models that more closely match the prototypical “three-equation New-Keyensian model” have often been used in the literature to argue that the effects of forward guidance are implausible. Therefore, to understand the role played by the frictions related to capital investment and utilization in matching the VAR impulse responses, we also estimate a small-scale version of our model without these frictions. First, we estimate a four-variable empirical VAR model with output, prices, the path factor, and the 2-year Treasury yield. We then ask a version of our theoretical model, which mimics a model without investment and capacity utilization adjustment, to match the forward guidance shock responses from this four-variable VAR. To mimic the three-variable New-Keynesian model, we calibrate the cost of adjusting investment and capacity utilization to arbitrarily high levels ( $\kappa = 1 \times 10^6$  and  $\sigma_\delta = 1 \times 10^6$ ) which, as we verified using simulations, implies that all of the variation in output comes from changes in consumption.

We find that the small-scale model is able to match the observed response of output, prices, interest rate futures, and Treasury yields to a forward guidance shock from the VAR. However, without real rigidities, this model requires a higher degree of nominal rigidities relative

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<sup>15</sup>We set the reaction coefficient on output growth equal to 0.1.

to our baseline model. In the estimation, we use the same priors for the remaining parameters as our baseline DSGE model with capital. In particular, we set the prior mode over the Calvo parameter  $\omega$  in our monthly model to 0.93 with a prior standard deviation of 0.008. At this prior mode, the average duration of prices is about 14 months, which is consistent with the evidence in Nakamura and Steinsson (2008) that the mean duration of prices from 1998-2005 was a little more than 1 year. Figure E.2 shows the resulting fit of the impulse responses for this alternative estimation. For much of the impulse response horizon, the responses of all of the variables are in the 90% probability intervals from the data. However, the model tends to underestimate the peak response of output and the trough in two-year Treasury rates. Also, the price response is higher in the model than is implied from the data, suggesting that the model fit is compromised by the tight prior we set over the Calvo parameter. Even with this tight prior, the posterior mode of the Calvo parameter,  $\omega = 0.97$ , implies an average duration of prices of 33 months.

For comparison, we also show responses when we set a looser prior and increase the prior standard deviation of the Calvo parameter  $\omega$  to 0.02 in Figure E.2. In this case, the posterior mode of the Calvo parameter increases to  $\omega = 0.98$ , implying an average duration of prices of 52 months. However, the fit improves considerably. Now, the model is able to come much closer to matching the peak response of output and the trough in the 2-year Treasury yield following a forward guidance shock. The model fit under this alternative prior is quite similar to our baseline model with capital, which implies an average duration of prices of 22 months in our baseline estimation. Thus, we conclude that a small-scale version of the New-Keynesian model can match the observed dynamics following a forward guidance shock. However, as Christiano, Eichenbaum and Evans (2005) found, without other rigidities (sticky wages, working capital, variable capacity utilization) the model may need a much larger degree of price rigidity.

## F Role of Investment Adjustment Costs

In our baseline model, firms face Christiano, Eichenbaum and Evans (2005)-type adjustment costs to changing investment in productive capital. We now provide some further details on how our estimated investment adjustment costs facilitate the model’s fit in other dimensions. In particular, we find that the degree of investment adjustment costs have important implications for the path of short-term policy rates and futures rates in the model. To illustrate this, we re-estimate our baseline model using a much tighter prior for the investment adjustment cost parameter  $\kappa$  (see Table (see Table F.1 for details). Figure F.1 below illustrates the resulting impulse responses using this tighter prior and compares them with our baseline results. As expected, the posterior mode for the investment adjustment cost parameter falls significantly using this alternative prior ( $\kappa = 8.6$ ) compared with our baseline estimate ( $\kappa = 36.8$ ). Relative to our baseline results, the peak response of investment is a bit larger and occurs sooner under the tight prior, which brings the response of investment closer to the VAR evidence. However, under the tight prior on  $\kappa$ , the response of futures rates (the path factor) in the model overshoots the empirical response and the response falls well outside of the VAR probability interval.

Intuitively, the Christiano, Eichenbaum and Evans (2005) investment adjustment cost specification, which we use in our model, creates delayed, hump-shaped responses in investment, and hence output. For lower values of the adjustment costs, Figure F.1 shows that investment and output rise more sharply following an expansionary forward guidance shock. As a result, in the re-estimated model with a tight prior on  $\kappa$ , futures rates (and hence future policy rates) rise more sharply and even overshoot their pre-shock baseline about 1 year after the initial forward guidance shock as the endogenous component of the central bank’s policy rule responds to the sharper rise in economic activity. The model’s prediction for futures rates when the investment adjustment costs parameter is constrained to be low is therefore

at odds with our VAR evidence which does not feature much of a overshoot of futures rates. Therefore, for the model to match the VAR evidence on the path of futures rates, a high degree of investment adjustment costs is selected. While this improvement in the fit of futures rates results in a marginally worse fit for the model's investment response, the path of futures rates is estimated more precisely than is the response of investment. Therefore, the estimation routine chooses (on the margin) to increase the value for the investment adjustment costs to facilitate fitting the path of futures rates.

To further illustrate this slight tension between fitting the path of futures rates and the response of investment, we re-estimate our structural model, this time asking the model to reproduce the response of consumption rather than investment. In particular, in our baseline empirical VAR, we replace our proxy for investment (core capital goods shipments) with consumption (real personal consumption expenditures). Then, we re-estimate our structural model. Figure F.2 below plots the resulting impulse responses from the re-estimated structural model (green dashed lines) and compares them with their empirical counterparts and Table F.1 shows the resulting parameter estimates. In addition, we also plot the impulse responses from our baseline estimated structural model (red dashed lines), for which we did not include consumption as a variable to match in the estimation routine.

While the re-estimated model without investment generally performs well in reproducing the empirical evidence, the estimated parameters highlight the trade-off between fitting the rate dynamics versus the response of investment. Since we are not asking the model to match the response of investment, the estimation routine chooses a larger value for the investment adjustment costs (and habits in consumption) in order to try and generate a delayed and hump-shaped responses for output and consumption. However, both our baseline estimation and this re-estimation without investment are generally able to reproduce the patterns we

observe in the empirical evidence, suggesting that this tension is not a binding constraint on the model’s ability to fit the data. Moreover, using a quarterly frequency rather than our baseline monthly frequency for our structural model, Figure 7 of the main text shows that the model-implied response of investment is much closer to its empirical counterpart in the quarterly-frequency model. These additional results suggest that any apparent tension between fitting investment and the path of futures rates becomes further relaxed when the model is specified at quarterly, rather than monthly, frequency.

## G Discussion of Estimated Policy Rule Parameters

In the baseline model, we estimate both a high degree of policy rate smoothing and a persistent forward guidance shock process. In this section, we illustrate that both of these features may not be strictly necessary to match our baseline empirical estimates. In particular, Figure G.1 shows that our model can generate an essentially identical fit if we restrict the forward guidance shock process to be IID (i.e. if we set  $\rho_\nu = 0$ ). Figure G.1 also illustrates that we find a very similar fit if we set a much lower prior over the degree of smoothing in the desired interest rate.

Our estimation procedure estimates the forward guidance shock in the model such that the change in the model-implied futures curve matches the movements in futures rates in our empirical VAR. To generate the forward guidance shock needed to achieve a given movement in future rates, the estimation routine can either simulate a small but persistent decline in the desired interest rate or a larger IID decline in the desired interest rate. The green-dashed line in Figure G.1 shows the estimated model-implied response to a forward guidance shock with  $\rho_\nu = 0$ . The fit under the version without any persistence in the shock process is nearly identical to the baseline model. The model achieves this fit by increasing  $\sigma_\nu = 0.71$ , in an annualized percentage rate, from  $\sigma_\nu = 0.08$  in the baseline model. This larger IID shock

fades more quickly but inherits some persistence through the smoothing parameter,  $\phi_r$ , in the policy rule. For the results shown in Figure G.1 we restrict all other parameters to be identical to the baseline model and simply re-estimate  $\sigma_\nu$ . However, we find similar results and model fit if we instead re-estimate all of the model's parameters while setting  $\rho_\nu = 0$ . These results illustrate that the model estimation doesn't rely on any particular value of  $\rho_\nu$  to match the dynamics of futures rates in the VAR impulse responses.

We can also find a similar model fit if we reduce the degree of smoothing in the desired policy rate. In particular, Figure G.1 shows the estimated model impulse response to a forward guidance shock when we re-estimate the model parameters and set a prior mode of  $\phi_r = 0.25$ . Interestingly, the estimation routine selects a posterior mode for  $\phi_r = 0.29$ , very near the prior mode. This finding suggests that the degree of interest rate smoothing is not well identified, as we discuss in Section 4.3 of the main text. However, as Figure G.1 shows, the overall fit of our model to an exogenous forward guidance shock does not rely on a particular assumption regarding the amount of history dependence in the policy rule.

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Table A.1: Comparison of Forward Guidance Shocks Series

Measure	FOMC Meetings	Event Window	Max horizon of futures	LIBOR Adjustment	# of factors	Sample
Bundick and Smith (2018) Path Factor	Scheduled	1 day	8-quarter	No	2	1994-2015
Nakamura and Steinsson (2018)	All	30 minute	4-quarter	No	1	1995-2014
	Scheduled	30 minute	4-quarter	No	1	2000-2014
Gurkaynak, Sack and Swanson (2005)	All	30 minute	4-quarter	No	2	1990-2004
Campbell et al. (2012)	All	1 day	4-quarter	Yes	2	1994-2007
	All	1 day	6-quarter	Yes	2	2007-2011
Campbell et al. (2017)		1 day	4-quarter (only)		0	

Table A.2: Ten Largest Observations of the Path Factor from January 1994 – November 2008

Date	Path Factor	GSS (2005) Path Factor <sup>b</sup>	Financial Market Commentary
May 17, 1994	-0.24	-0.12	Statement signals a pause in the tightening cycle by announcing that “These [rate increases] substantially remove the degree of monetary accommodation ...”
July 6, 1995 <sup>a</sup>	-0.22	-0.21	First easing after long (seventeen-month) series of tightenings raises expectations of further easings; statement notes that inflationary pressures have receded
Jan 28, 2004 <sup>a</sup>	0.21	0.23	Statement drops commitment to keep policy unchanged for a “considerable period,” bringing forward expectations of future tightenings
May 6, 2003 <sup>a</sup>	-0.20	-0.15	Statement announces balance of risks now dominated by risk of “an unwelcome substantial fall in inflation”
June 25, 2003	0.17	0.05	FOMC cuts funds rate to 1% but some expected a cut to 0.75% leading to some speculation that there would be no further easing.
March 18, 2008	0.17	—	Statement adds more emphasis to concerns around elevated inflation, announces that “uncertainty about the inflation outlook has increased”
December 11, 2007	-0.17	—	Statement replaces risk assessment that, “the upside risks to inflation roughly balance the downside risks to growth” with an announcement of increased “uncertainty surrounding the outlook for economic growth and inflation.”
August 13, 2002 <sup>a</sup>	-0.17	-0.20	Statement announces balance of risks has shifted from neutral to economic weakness
October 31, 2007	0.16	—	Statement announces “the upside risks to inflation roughly balance the downside risks to growth,” reducing prospect of near-term easing
August 16, 1994	-0.16	-0.05	Statement announces 0.5% increase in the funds rate but signals no further imminent increases by announcing that, “these actions are expected to be sufficient, at least for a time, to meet the objective of sustained, noninflationary growth.”

[a] This event and the financial market commentary is included in Table 4 of Gurkaynak, Sack and Swanson (2005).

[b] These values of the Path Factor from Gurkaynak, Sack and Swanson (2005) are scaled versions of the values taken from their online appendix. We scale their measure using the estimates obtained from regressing our path factor on their measure and a constant.

Table F.1: Additional Discussion of the Role of Investment Adjustment Costs

		<b>Baseline Estimates</b>				
Parameter	Description	Distribution	Prior		Posterior	
			Mode	Std. Dev.	Mode	Std. Dev.
b	Habit Persistence	Beta	0.50	0.25	0.8898	0.0146
$\omega$	Calvo Probability	Beta	0.93	0.01	0.9558	0.0015
$\chi$	Degree of Lagged Indexation	Beta	0.50	0.25	0.0358	0.0299
$\phi_r$	Policy Rate Smoothing	Beta	0.95	0.25	0.9442	0.0021
$\kappa$	Investment Adjustment	Gamma	2.48	60.0	36.7530	2.3256
$\sigma_\delta$	Capacity Utilization Curvature	Gamma	0.01	60.0	0.0003	0.0002
$\rho_\nu$	Policy Shock Persistence	Beta	0.50	0.25	0.8358	0.0055
$\sigma_\nu$	Std. Dev. of Policy Shock (APR)	Gamma	0.25	12	0.0850	0.0035

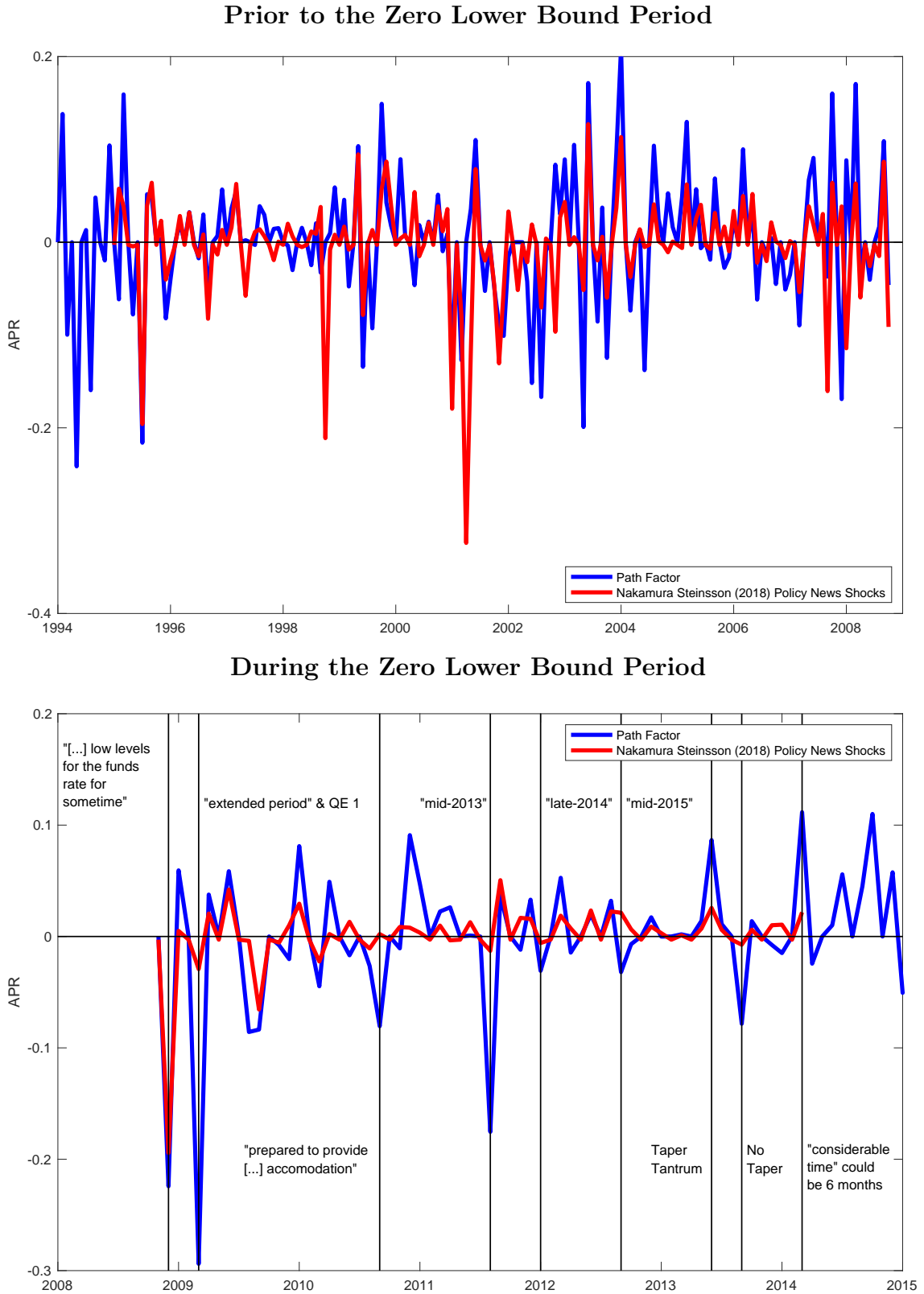
**Estimates with a Tighter Prior on Investment Adjustment Cost:  $\kappa$**

Parameter	Description	Distribution	Prior		Posterior	
			Mode	Std. Dev.	Mode	Std. Dev.
b	Habit Persistence	Beta	0.50	0.25	0.8644	0.0061
$\omega$	Calvo Probability	Beta	0.93	0.01	0.9439	0.0006
$\chi$	Degree of Lagged Indexation	Beta	0.50	0.25	0.0327	0.0052
$\phi_r$	Policy Rate Smoothing	Beta	0.95	0.25	0.8941	0.0021
$\kappa$	Investment Adjustment	Gamma	2.48	0.43	8.5891	0.3625
$\sigma_\delta$	Capacity Utilization Curvature	Gamma	0.01	60.0	0.0003	0.0000
$\rho_\nu$	Policy Shock Persistence	Beta	0.50	0.25	0.7758	0.0061
$\sigma_\nu$	Std. Dev. of Policy Shock (APR)	Gamma	0.25	12	0.3860	0.0195

**Estimates Matching the Response of Consumption Instead of Investment**

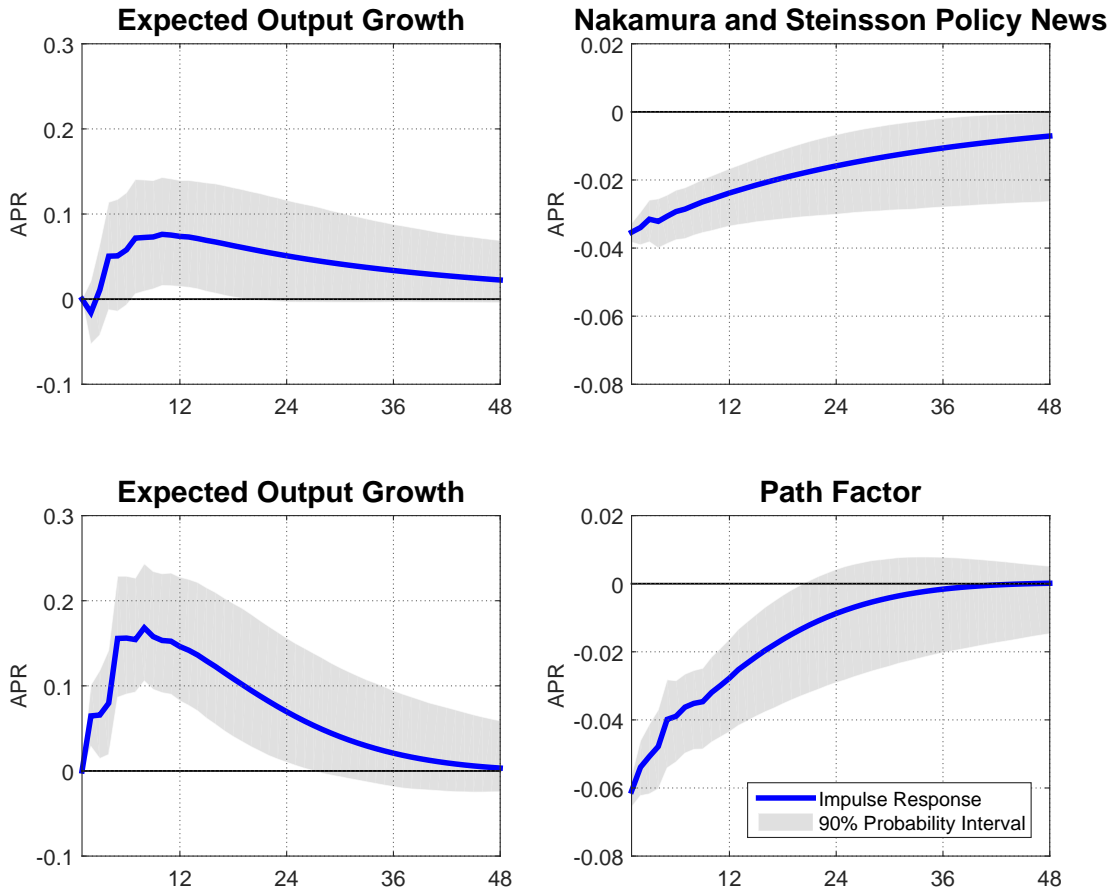
Parameter	Description	Distribution	Prior		Posterior	
			Mode	Std. Dev.	Mode	Std. Dev.
b	Habit Persistence	Beta	0.50	0.25	0.9463	0.0053
$\omega$	Calvo Probability	Beta	0.93	0.01	0.9586	0.0013
$\chi$	Degree of Lagged Indexation	Beta	0.50	0.25	0.0277	0.0282
$\phi_r$	Policy Rate Smoothing	Beta	0.95	0.25	0.8731	0.0038
$\kappa$	Investment Adjustment	Gamma	2.48	60.0	44.0459	2.1820
$\sigma_\delta$	Capacity Utilization Curvature	Gamma	0.01	60.0	0.0000	0.0002
$\rho_\nu$	Policy Shock Persistence	Beta	0.50	0.25	0.9380	0.0023
$\sigma_\nu$	Std. Dev. of Policy Shock (APR)	Gamma	0.25	12	0.0933	0.0036

Figure A.1: Comparison of Nakamura and Steinsson (2018) & Our Path Factor



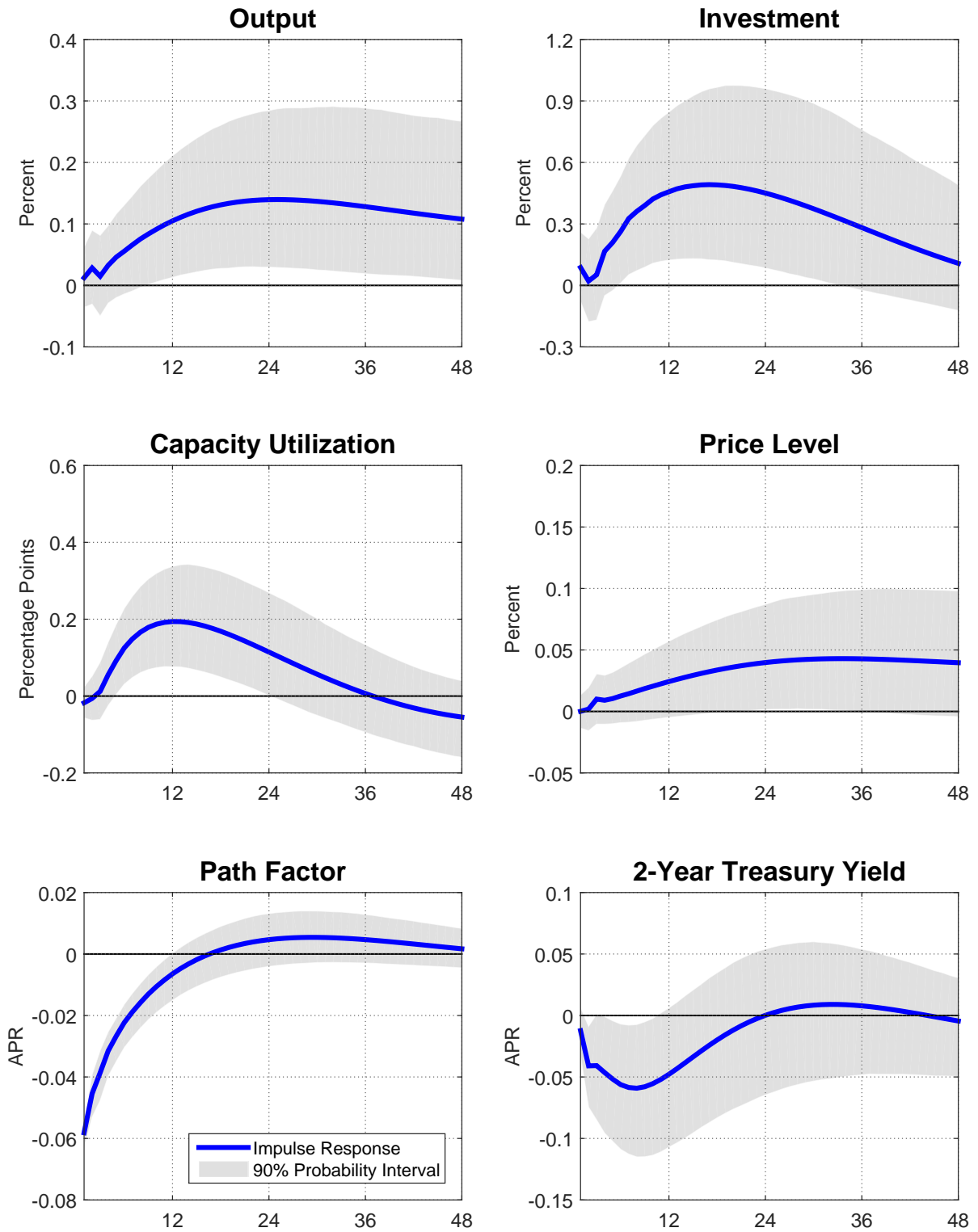
Note: The blue line denotes our forward guidance shock series (the path factor) and the red line denotes the policy news shock series from Nakamura and Steinsson (2018) scaled to be comparable to our series.

Figure A.2: Forward Guidance Shock Impulse Responses for Macroeconomic Survey Data



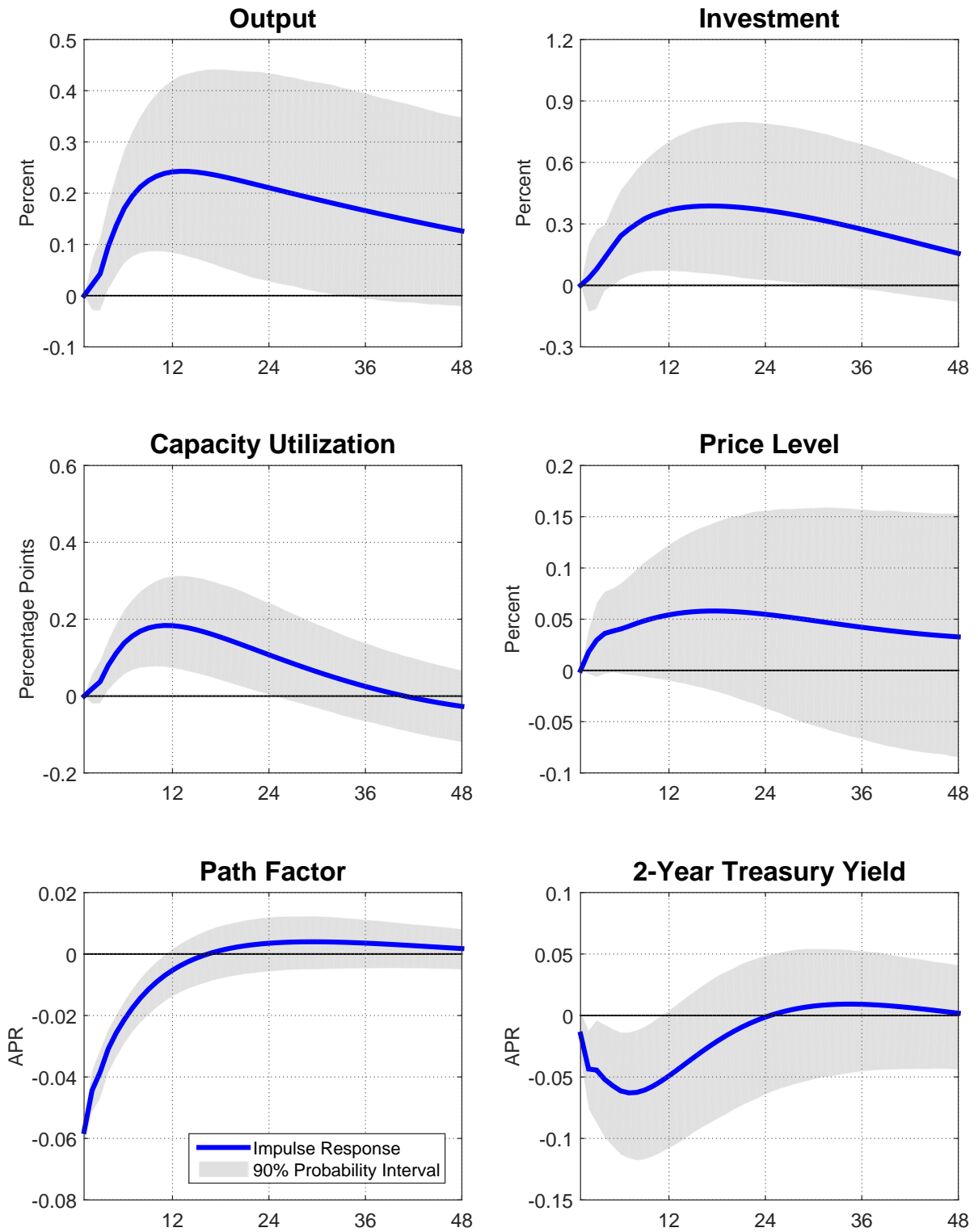
Note: Each row denotes the estimated impulse responses and probability interval of the posterior distribution to a one standard deviation forward guidance shock from a different empirical specification. The first row shows the specification using the Nakamura and Steinsson (2018) policy news shock series and the second row shows the specification using our forward guidance shock series (the path factor). Expected output growth is measured as in Nakamura and Steinsson (2018) as the average annualized growth rate forecasted for the current quarter, 1-quarter ahead, and 2-quarters ahead.

Figure B.1: Empirical Impulse Responses with Policy Ordered First



Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

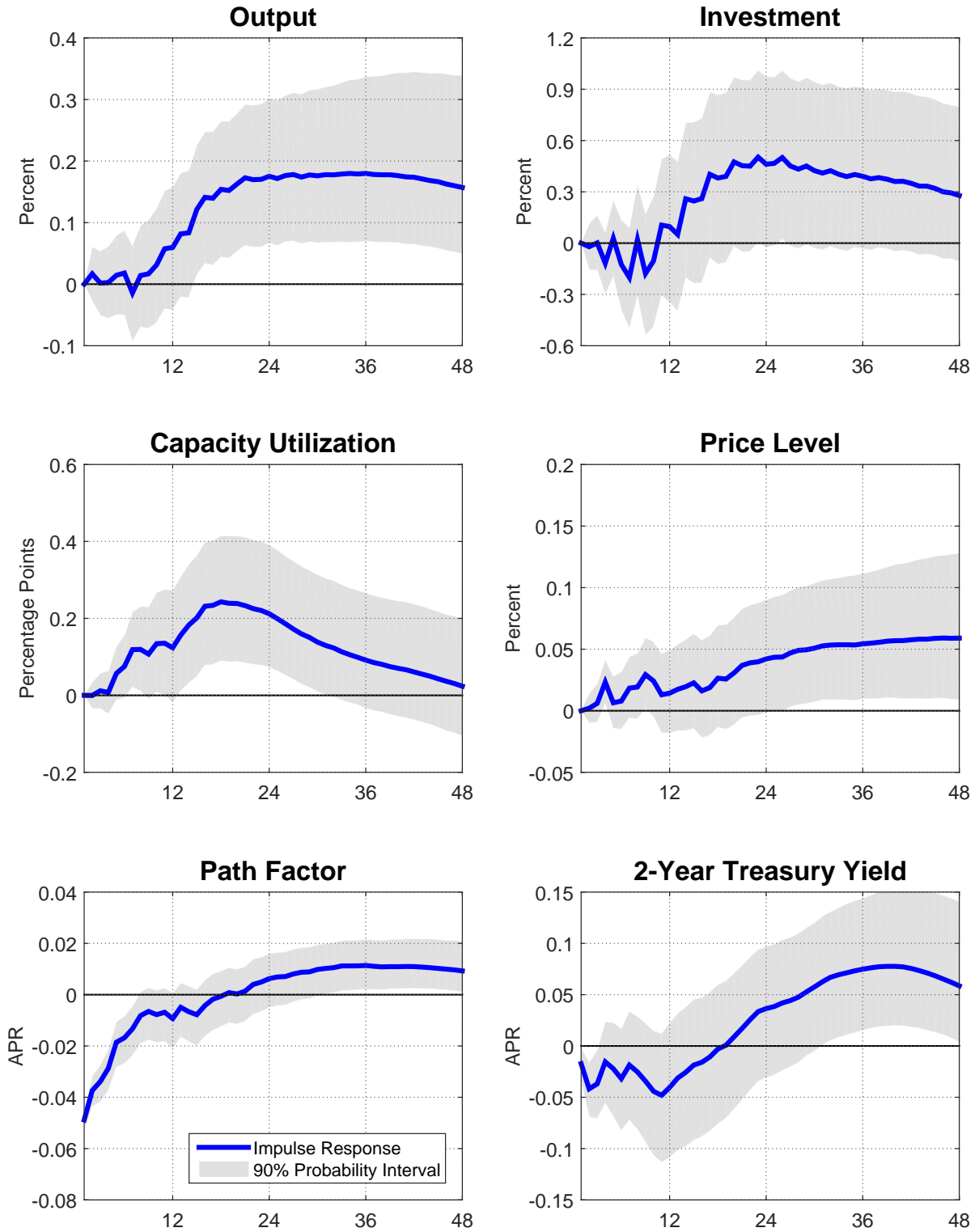
Figure B.2: Empirical Impulse Responses using Industrial Production & CPI



Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

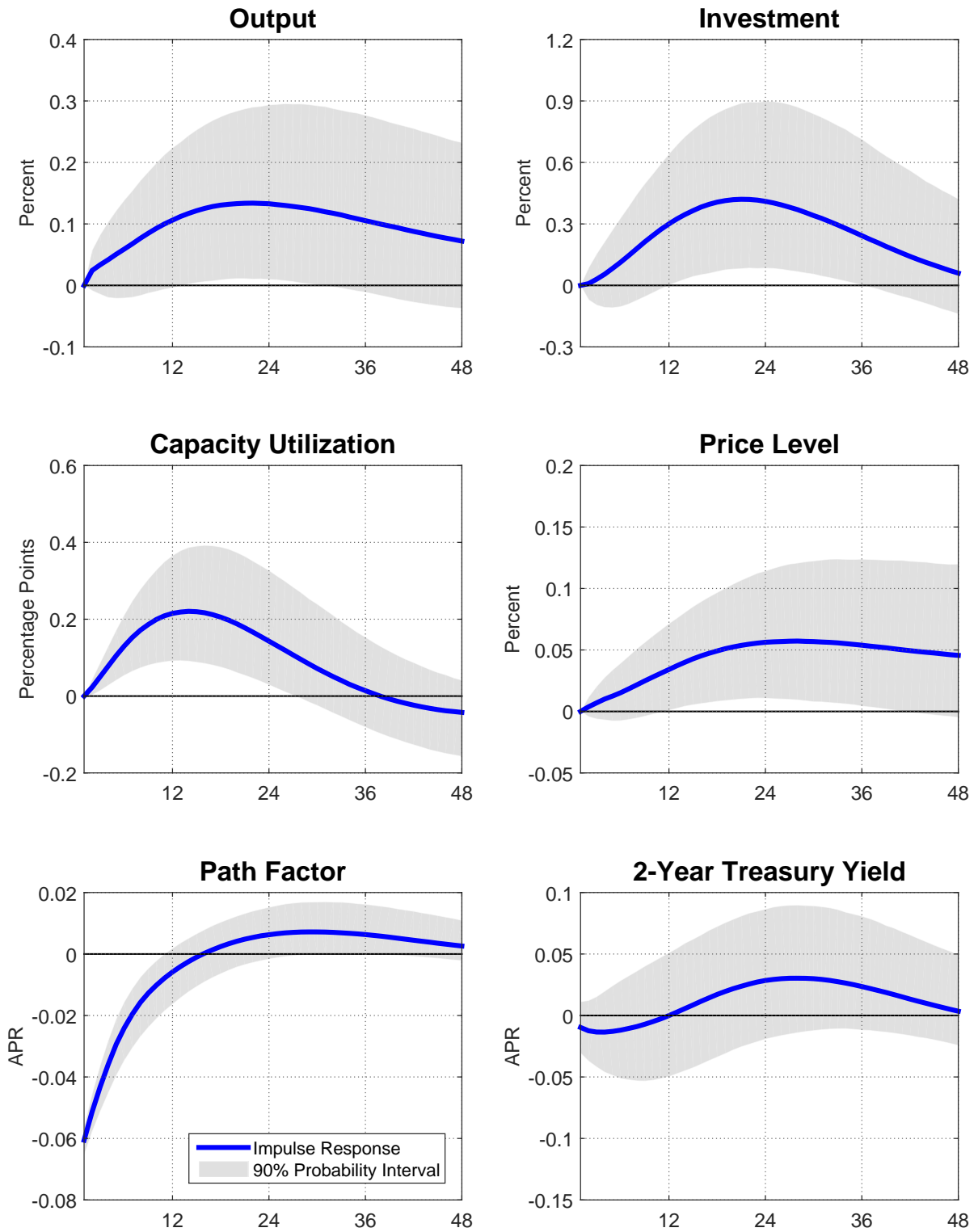


Figure B.3: Empirical Impulse Responses with 12 Lags in the VAR



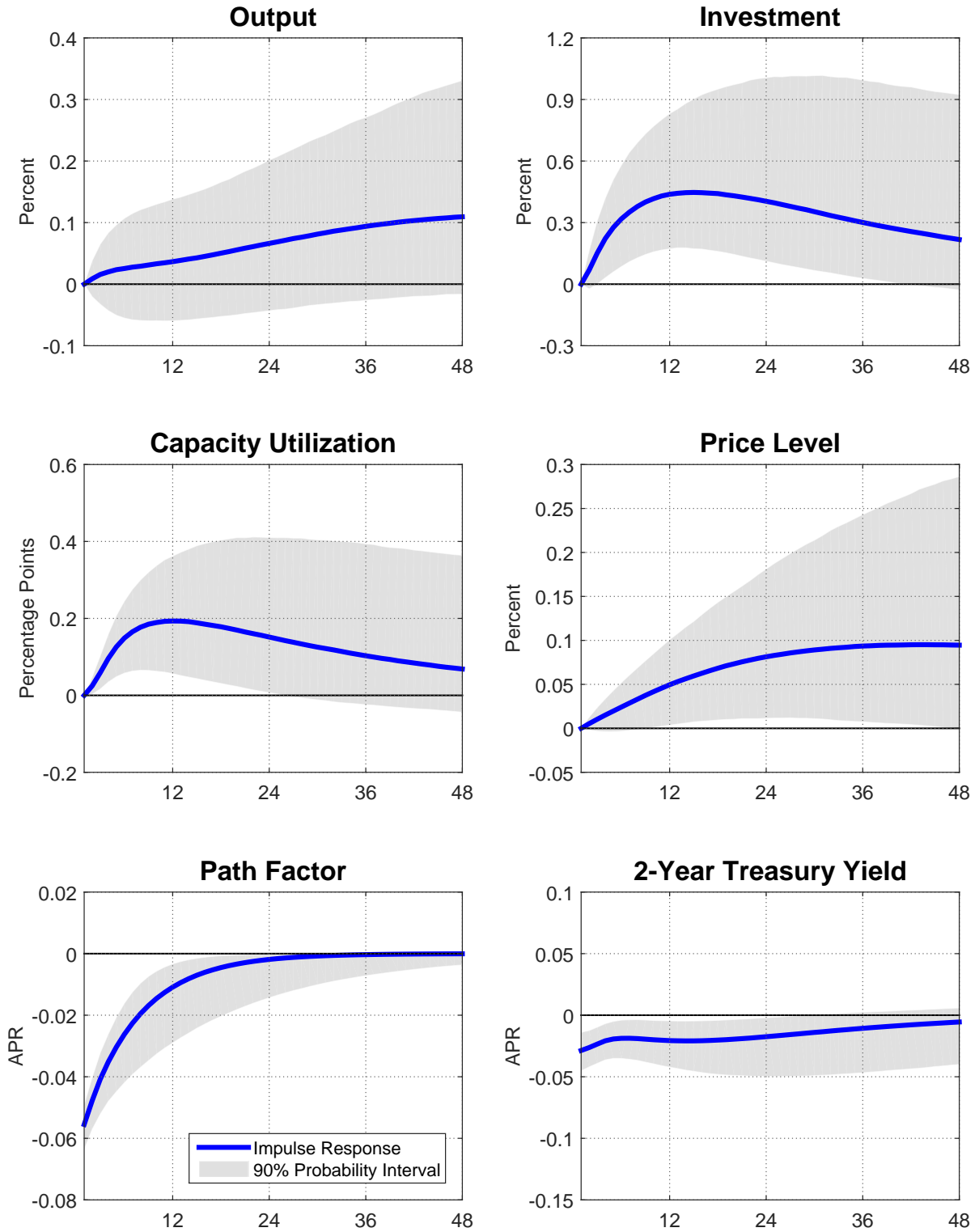
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure B.4: Empirical Impulse Responses using Minnesota Prior with 13 Lags



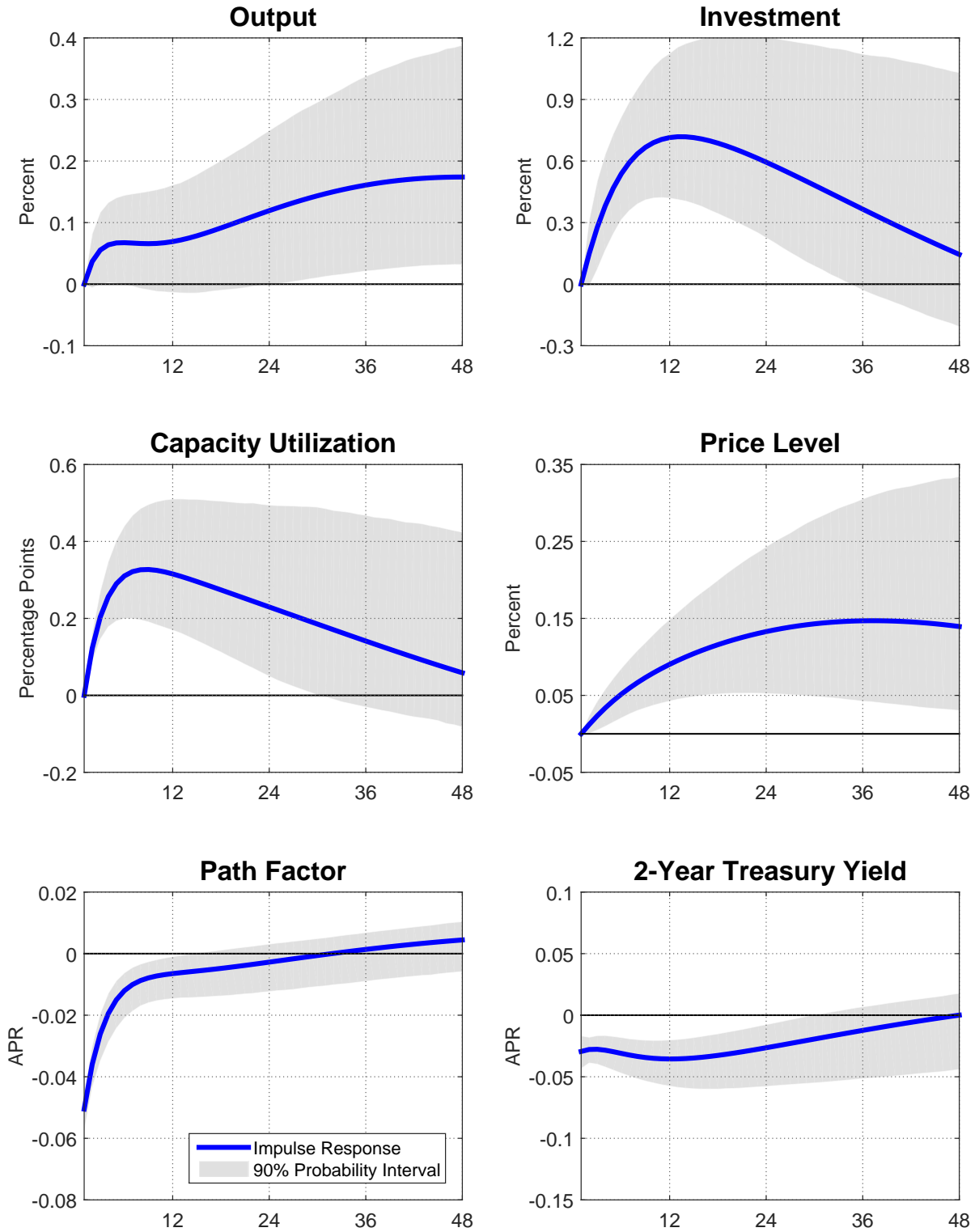
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure B.5: Empirical Impulse Responses with Policy Surprises Treated as Exogenous



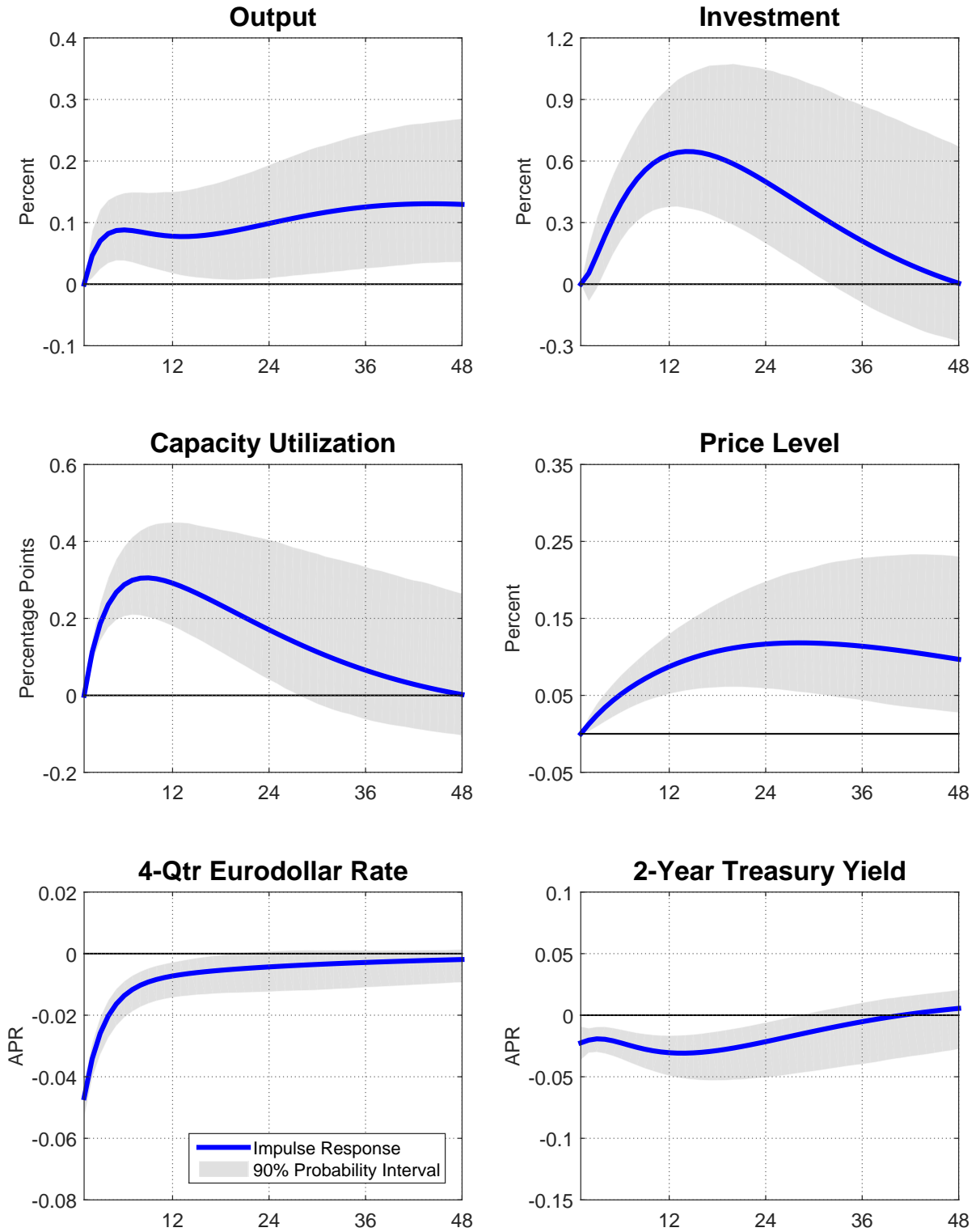
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure B.6: Empirical Impulse Responses using Uninformative Prior



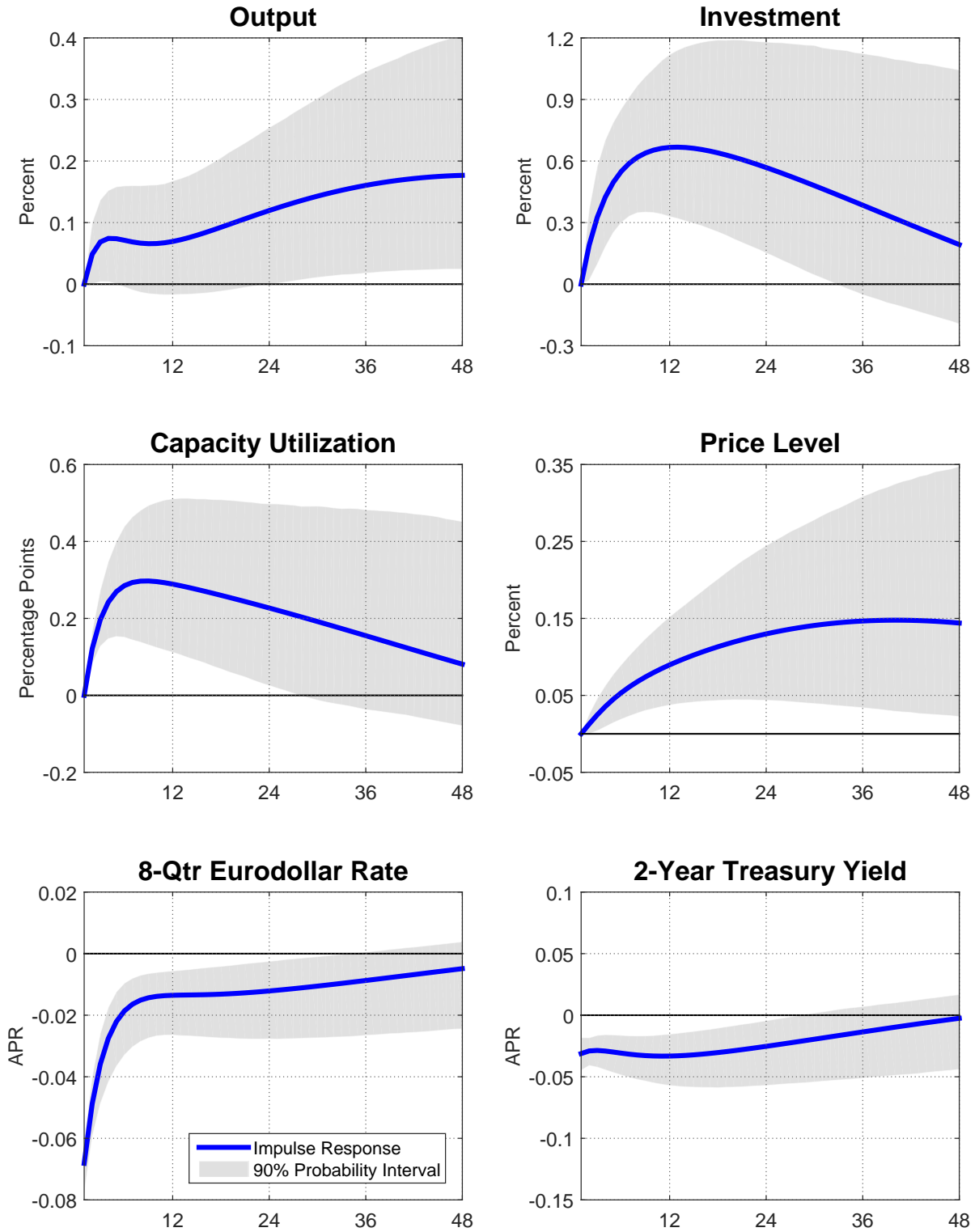
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure B.7: Empirical Impulse Responses using 4-Quarter Ahead Eurodollar Rates



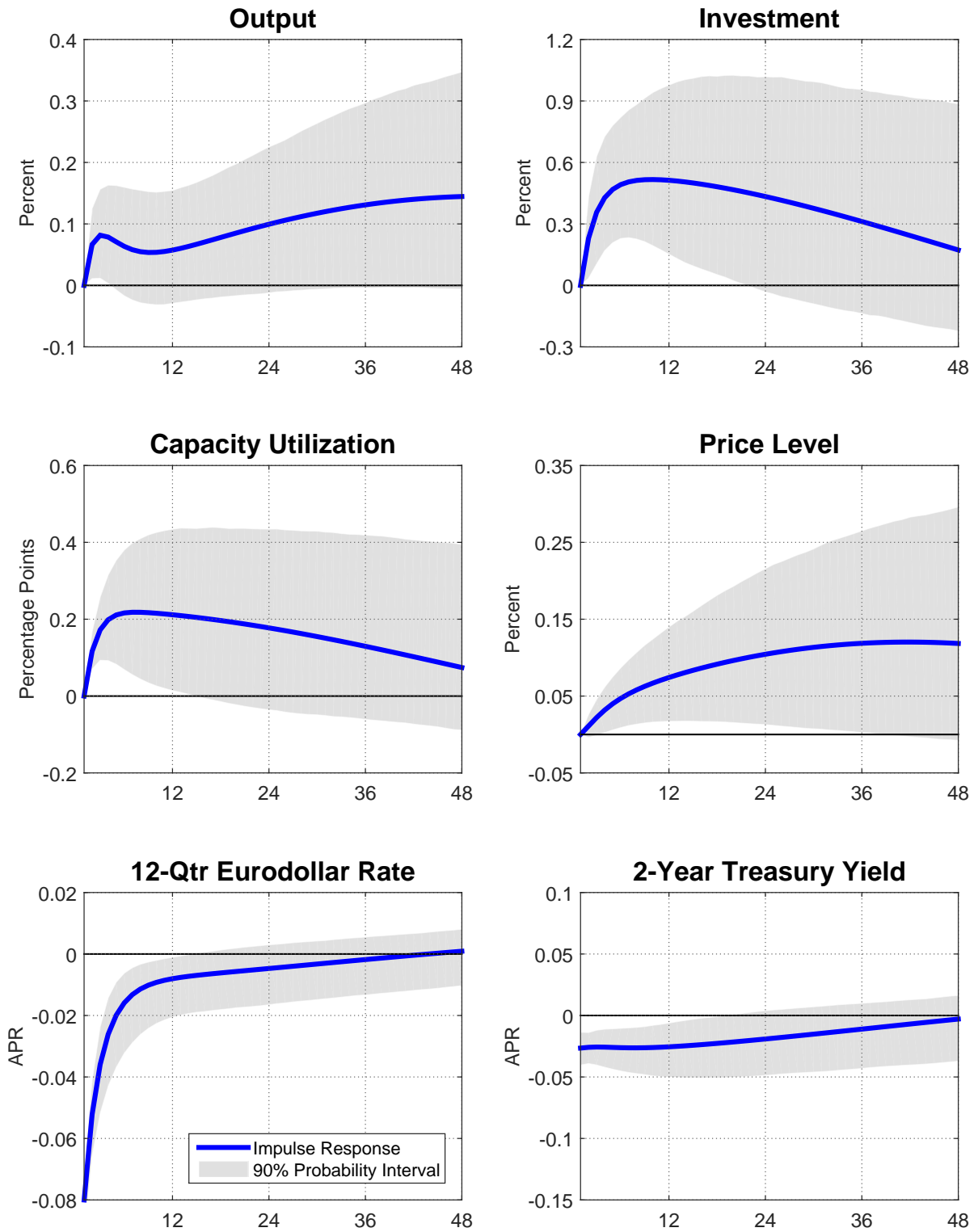
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure B.8: Empirical Impulse Responses using 8-Quarter Ahead Eurodollar Rates



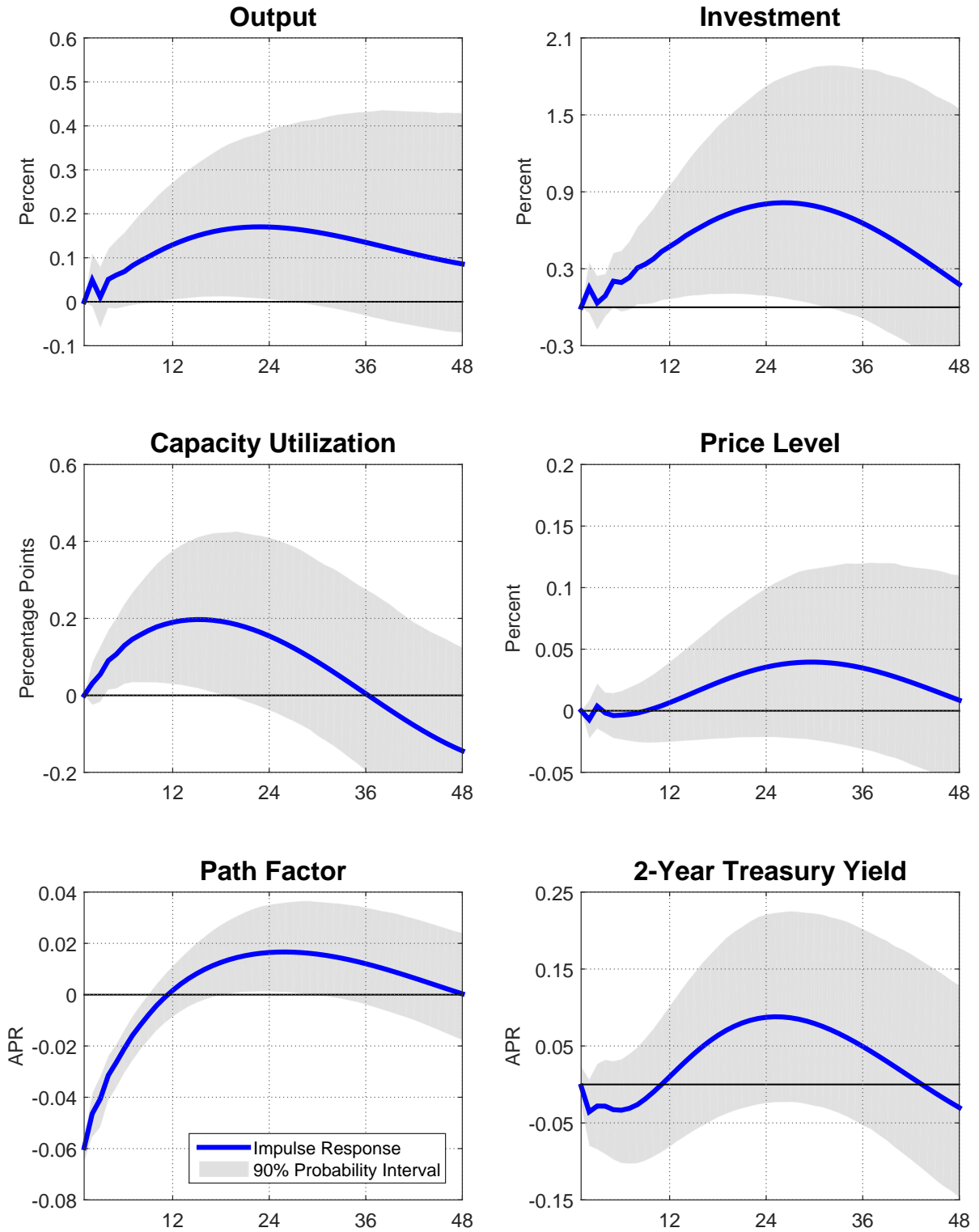
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure B.9: Empirical Impulse Responses using 12-Quarter Ahead Eurodollar Rates



Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

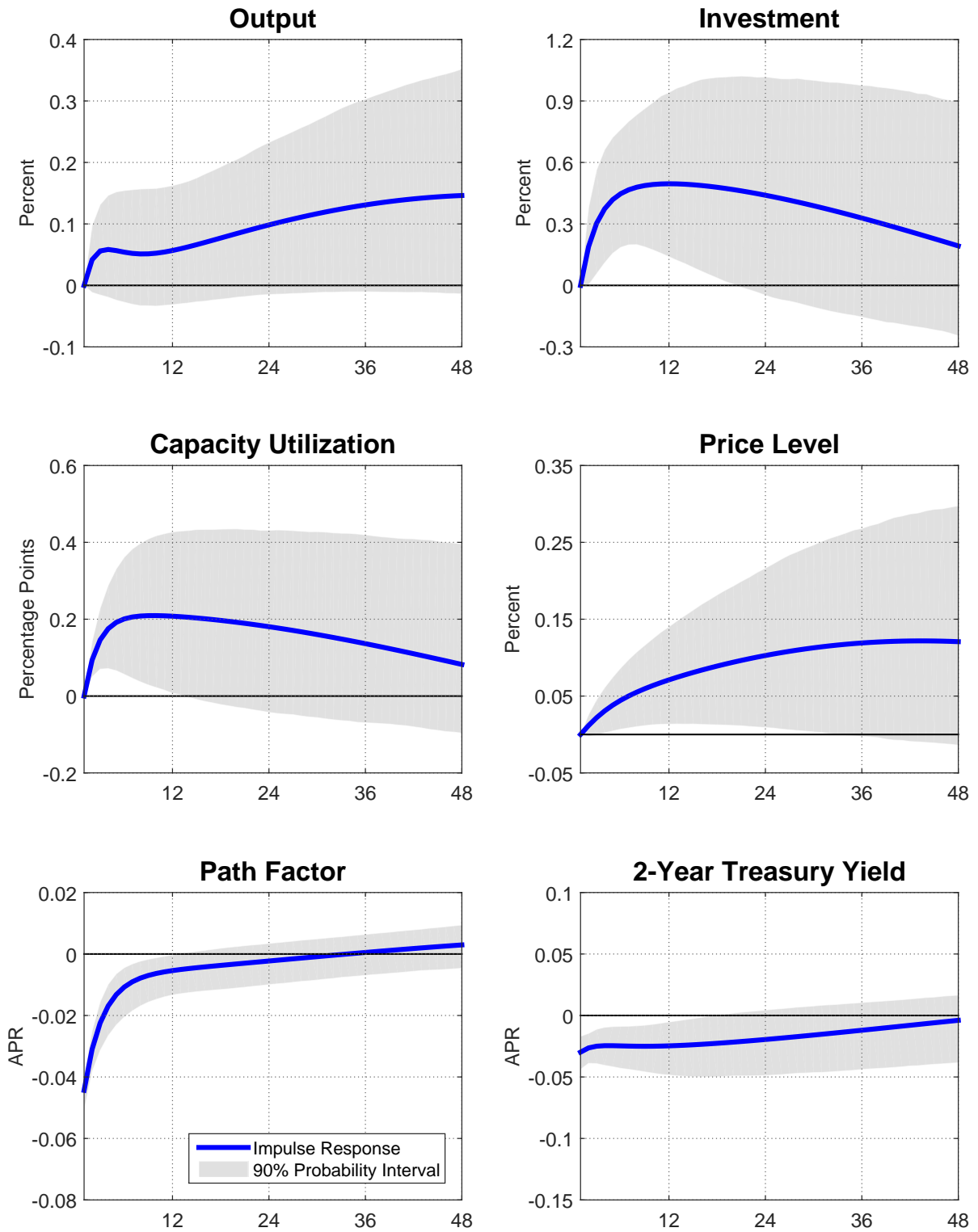
Figure B.10: Empirical Impulse Responses Before Onset of Zero Lower Bound



Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

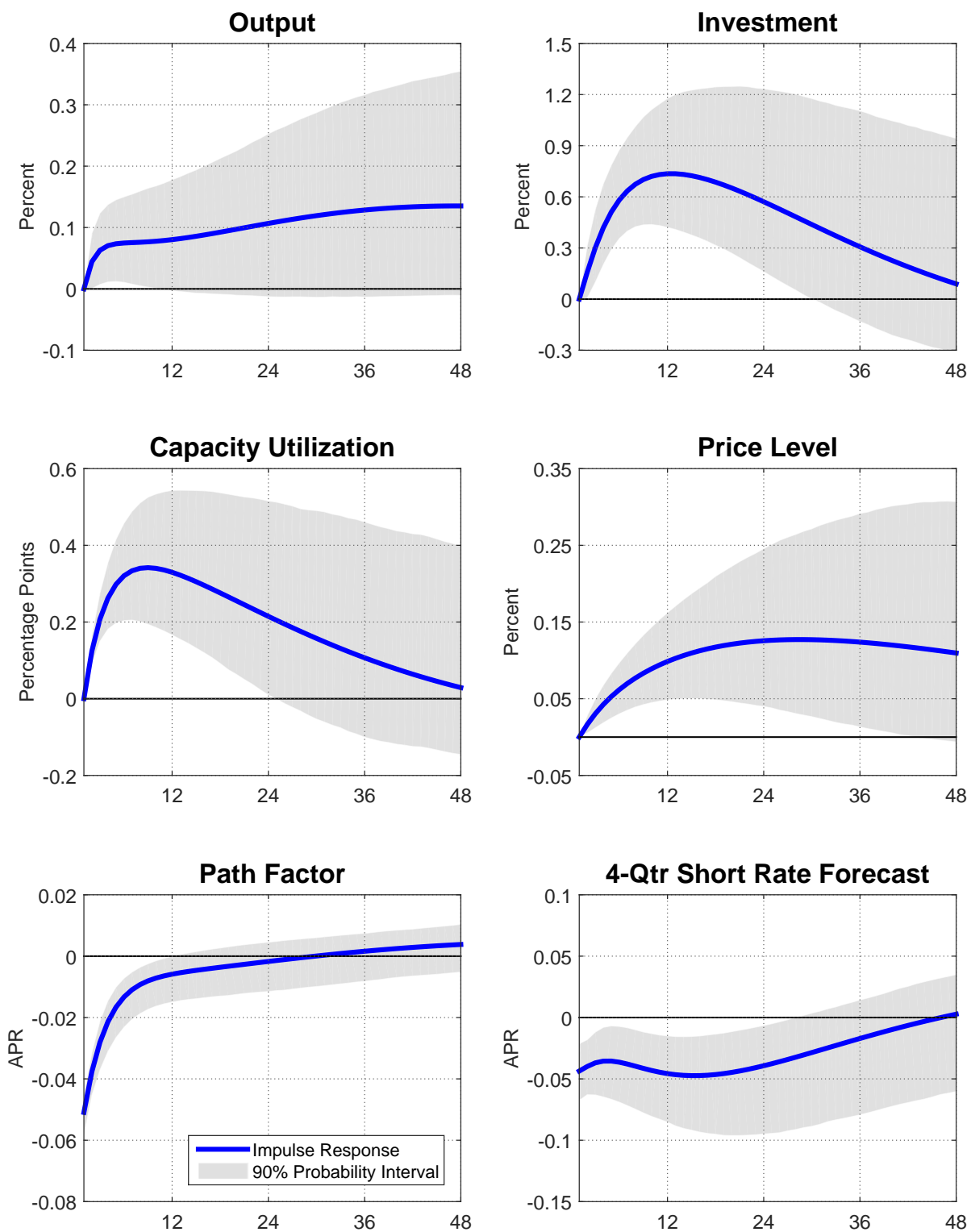


Figure B.11: Empirical Impulse Responses Dropping Key LSAP Announcements



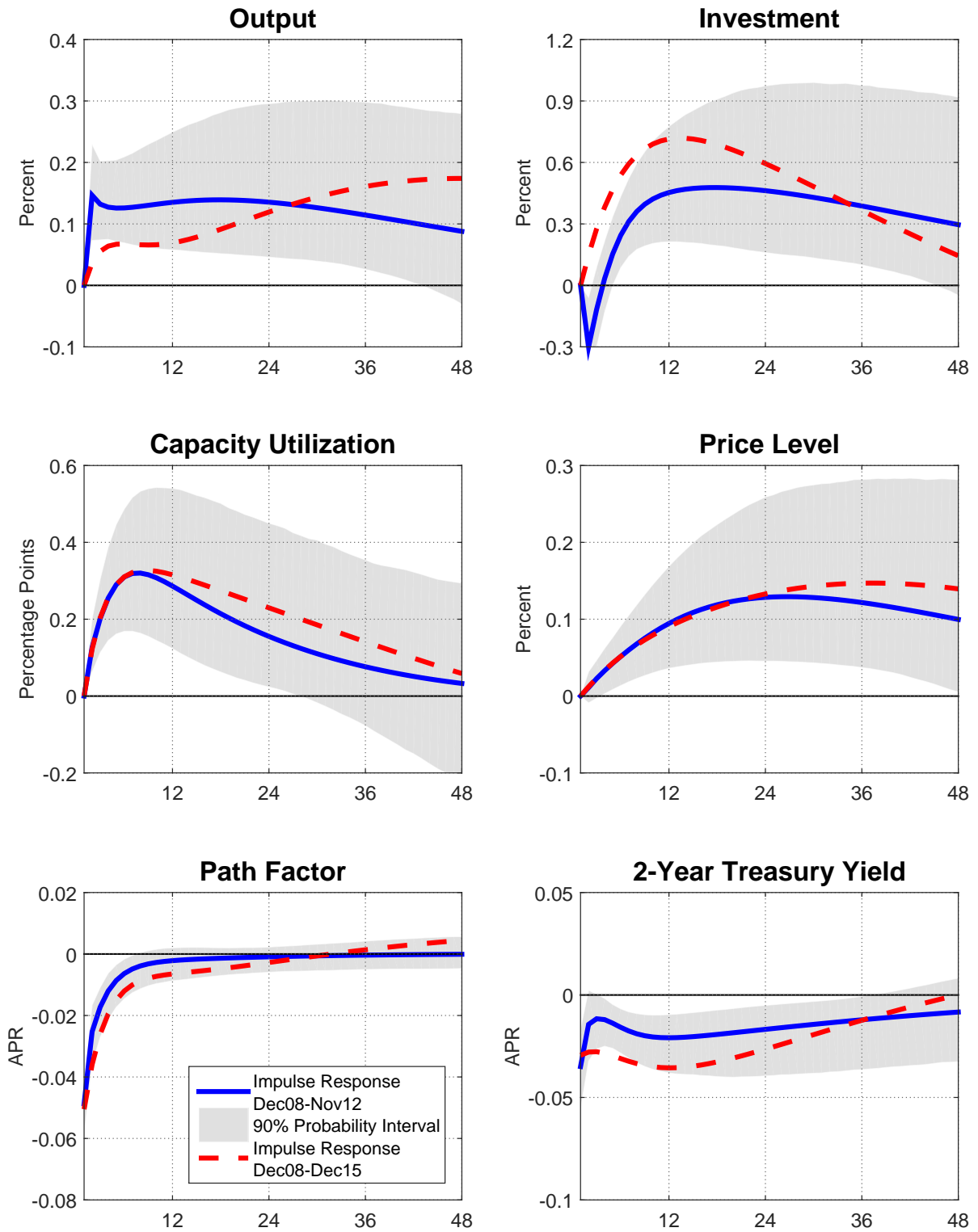
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure B.12: Empirical Impulse Responses Including Survey Forecasts of Interest Rates



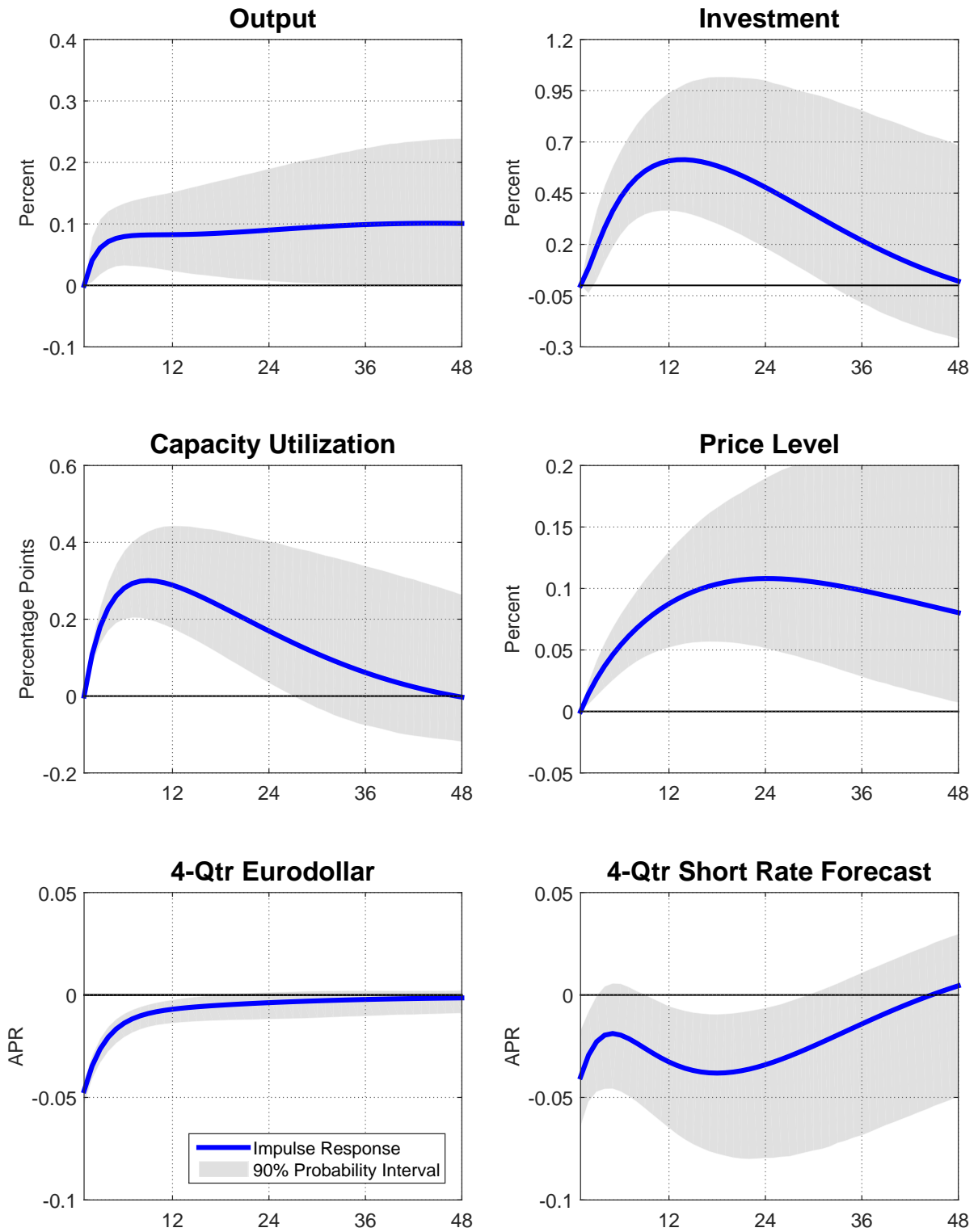
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure B.13: Empirical Impulse Responses Prior to Adoption of State-Dependent Guidance



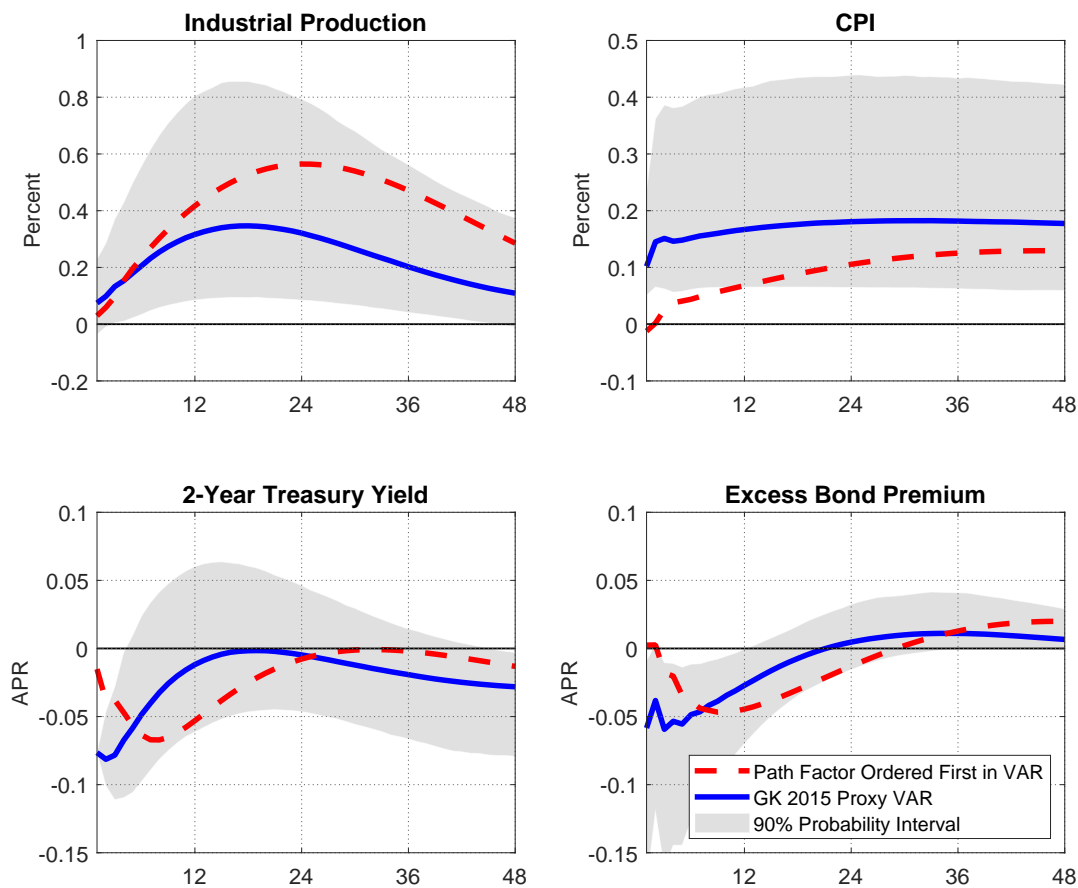
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure B.14: Empirical Impulse Response: Comparing 4-Qtr Ahead Survey & Eurodollars



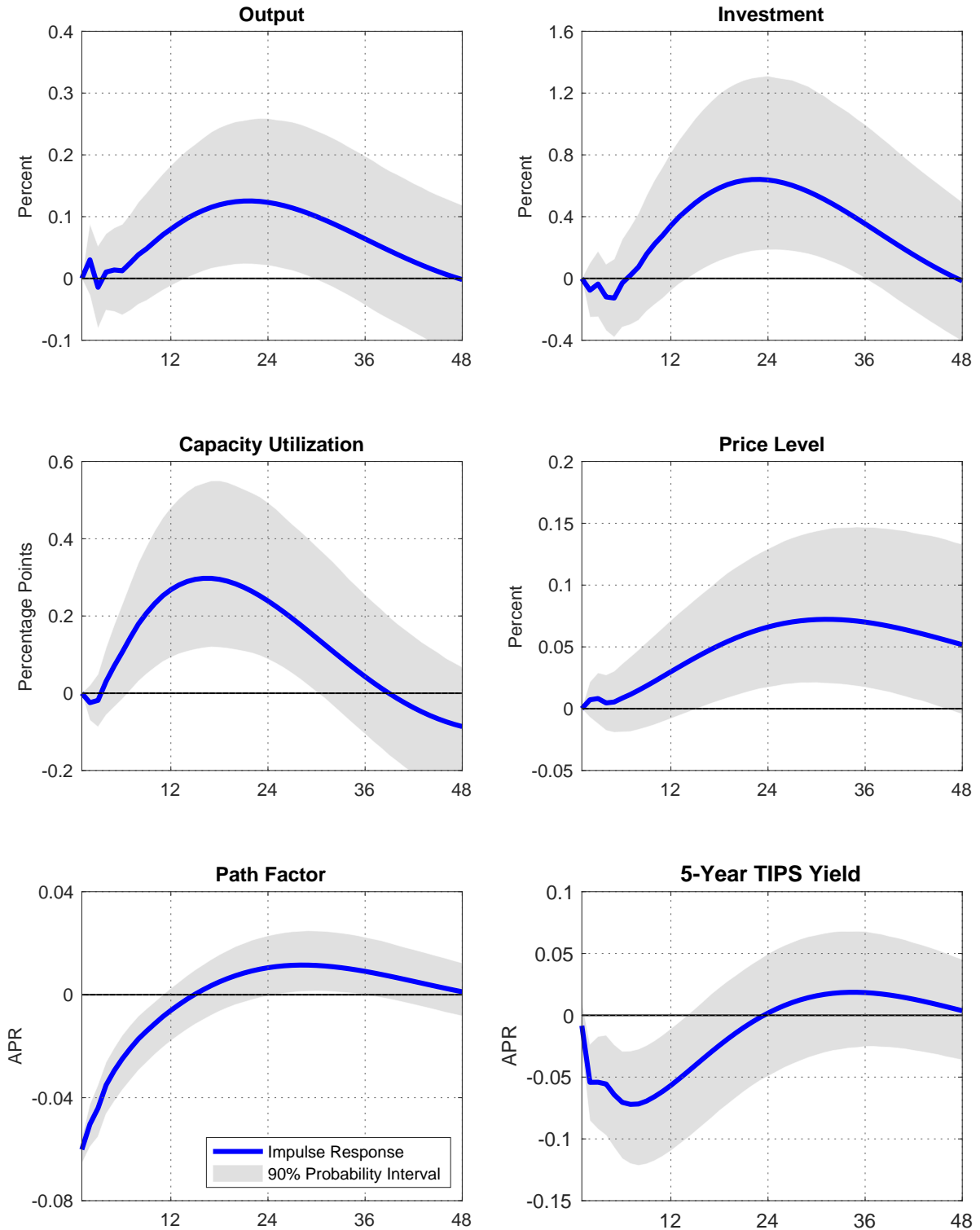
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure B.15: Impulse Responses for Forward Guidance Shocks: Gertler and Karadi (2015) Proxy VAR Approach vs. Including the Cumulative Sum of the Path Factor in the VAR



Note: The solid blue lines denote the impulse responses using the Gertler and Karadi (2015) proxy VAR approach from Figure 8 of their paper. The associated confidence intervals are shown by the gray shaded regions using their wild bootstrap procedure. The dashed red lines show the impulse responses from a five variable VAR which adds to these four variables the cumulative sum of our path factor series which is then ordered first. The impulse responses from the two approaches are scaled to generate the same (cumulative) movement in the 2-year Treasury yield over the 48 periods of the impulse response.

Figure B.16: Empirical Impulse Responses Including Real Treasury Yields



Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution. Due to the availability of Treasury-Inflation Protected Securities (TIPS) data, our sample for the empirical Bayes prior begins in January 1999.

Figure D.1: Impulse Responses Under Desired Rate & News Shock Specifications

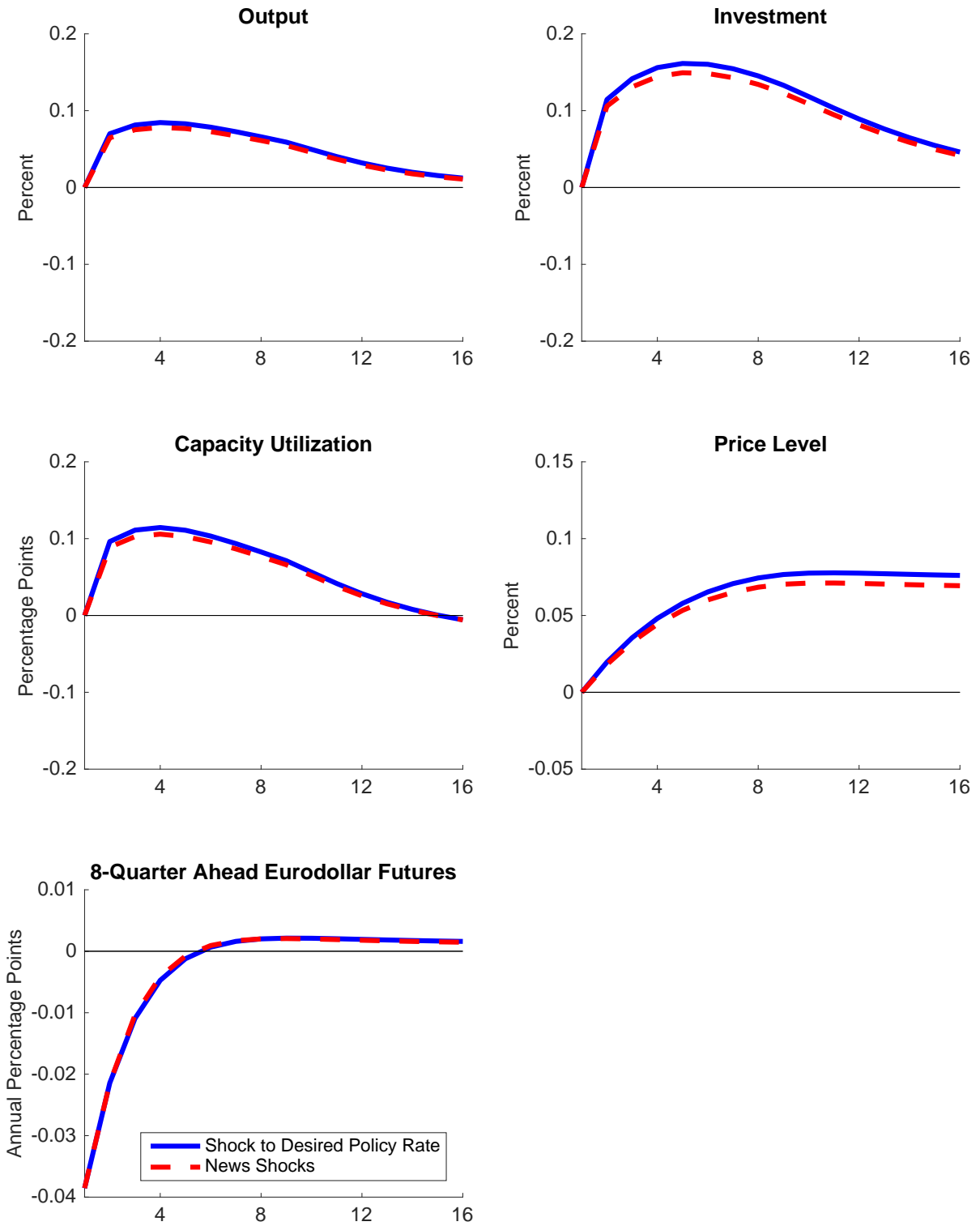
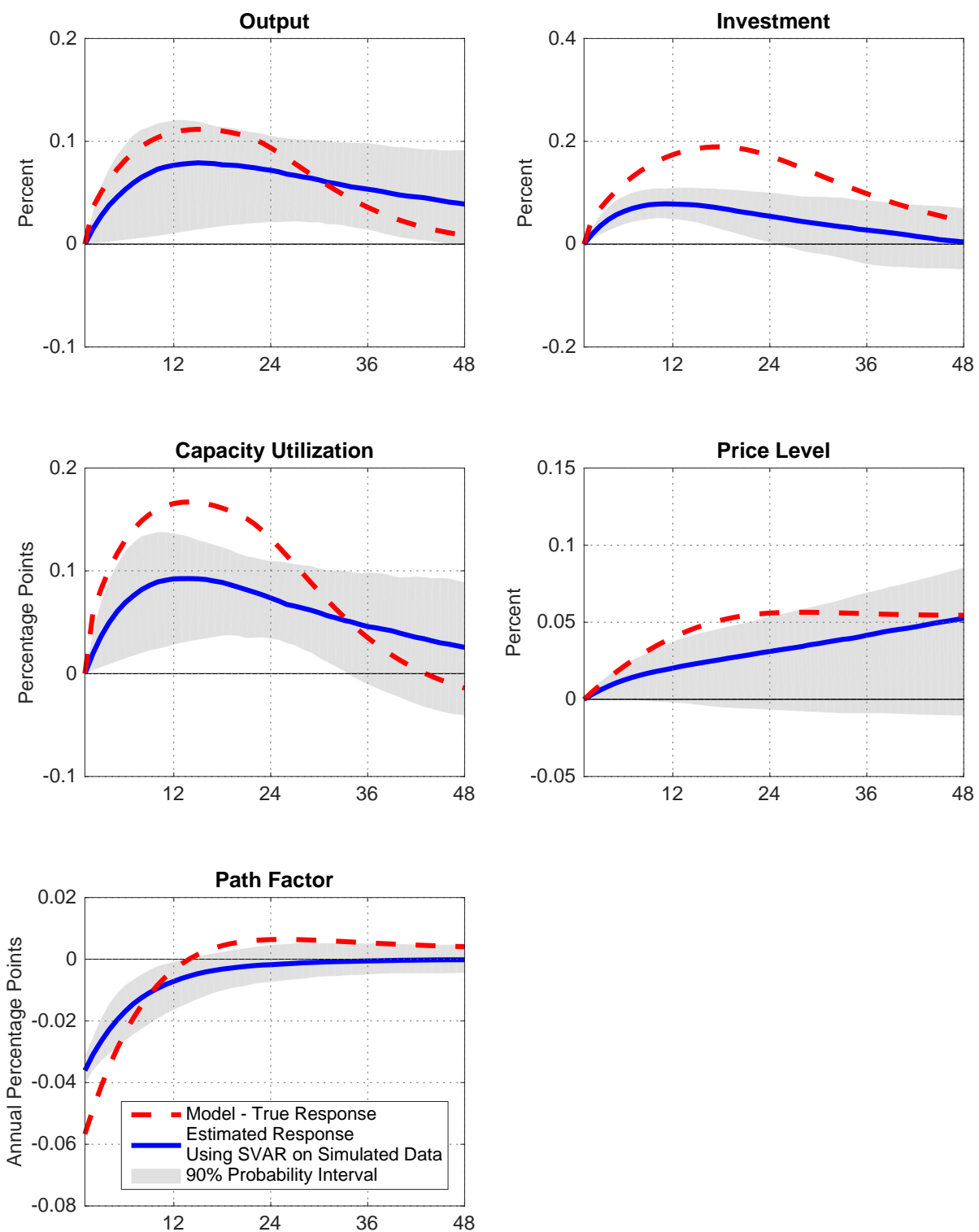


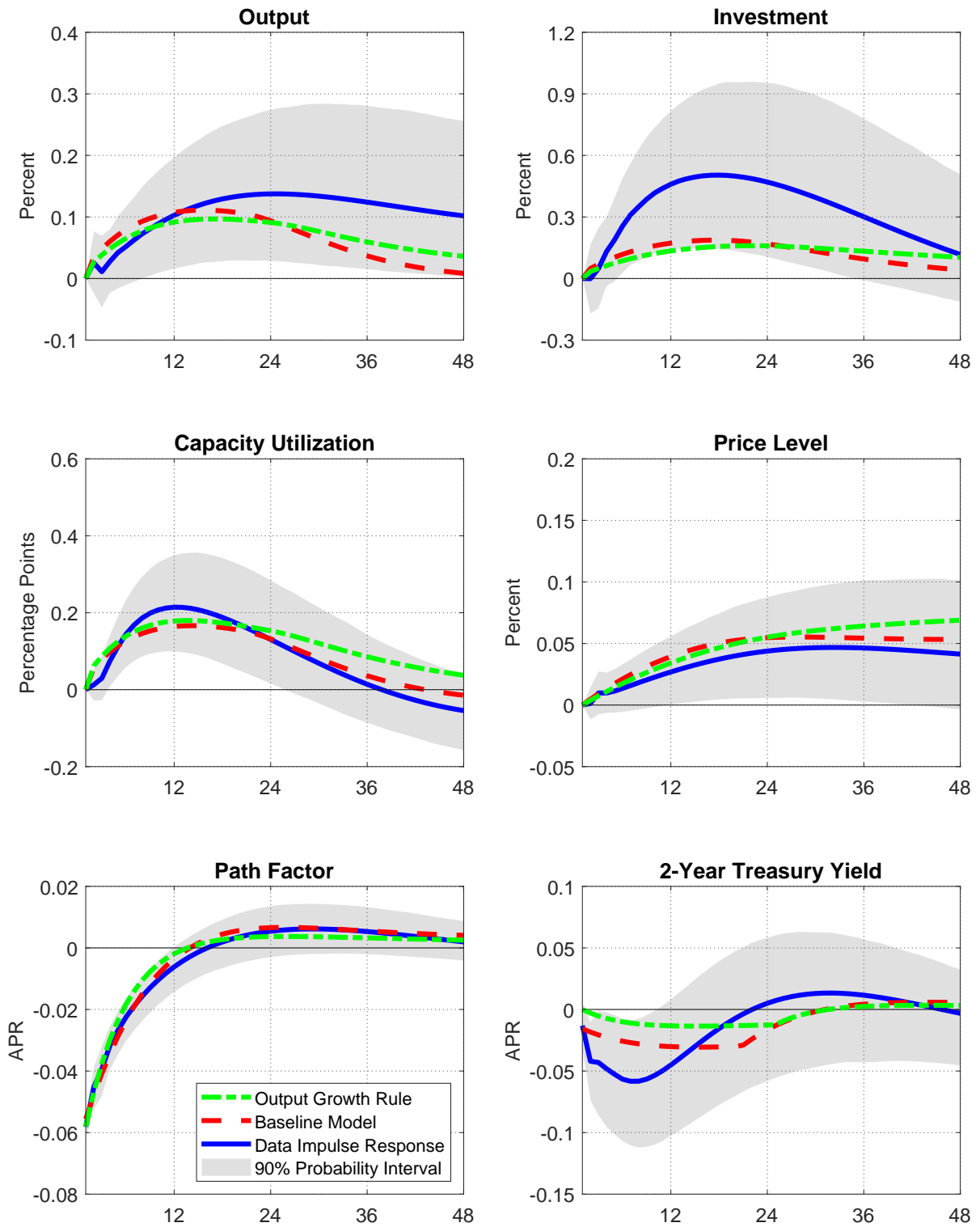
Figure D.2: Estimating Structural Vector Autoregressions on Simulated Data from the Model



Note: The dashed red line denotes the impulse response to a one standard deviation forward guidance shock in the model. The solid blue line denotes the median impulse response across 1000 estimates when we use data simulated from the model to estimate a VAR. The shaded areas denote the 90% interval across these 1000 estimates.

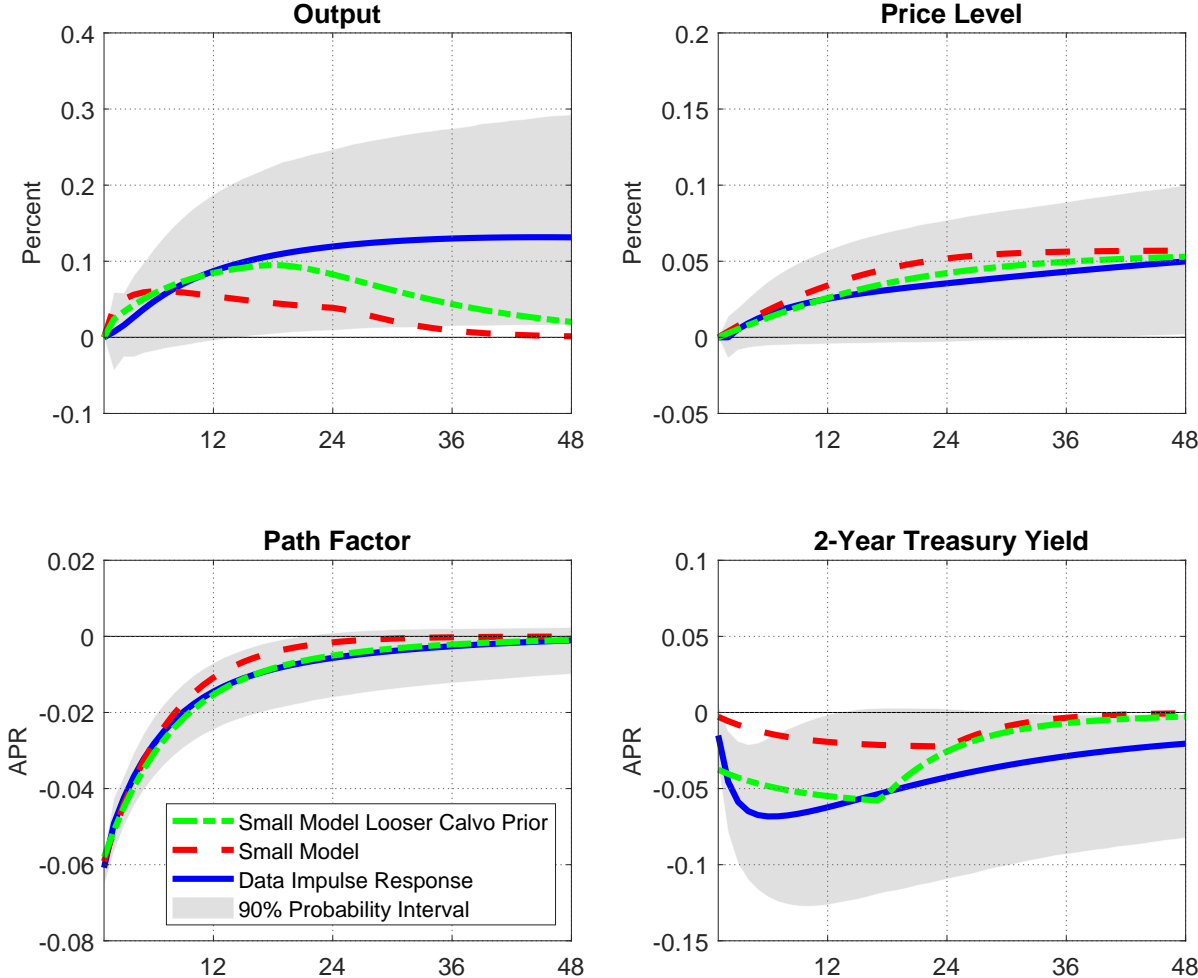


Figure E.1: Empirical & Model Impulse Responses Using an Output Growth Rule



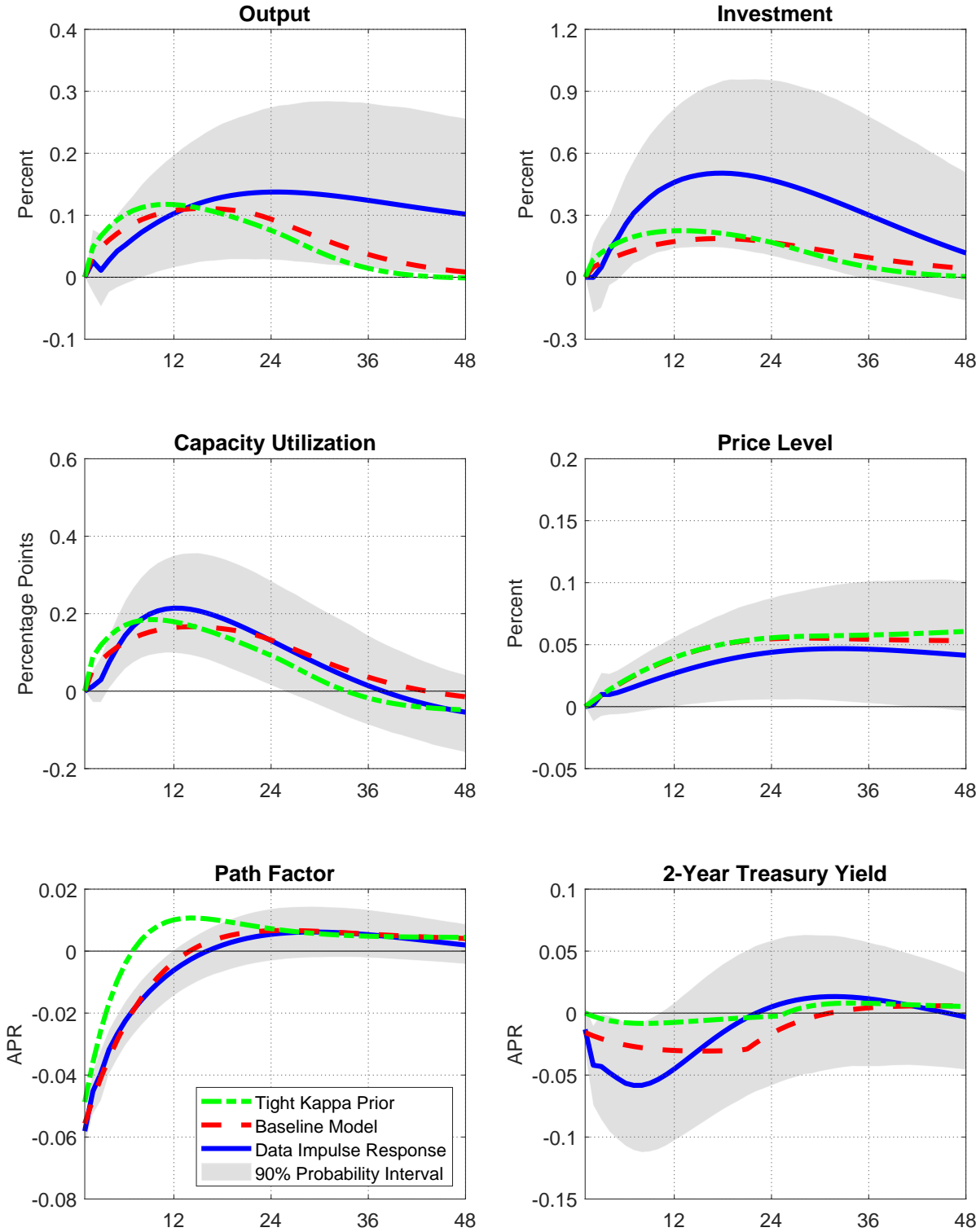
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution. The dashed lines denote model-implied impulse responses.

Figure E.2: Empirical & Model Impulse Responses in Small Scale New-Keynesian Model



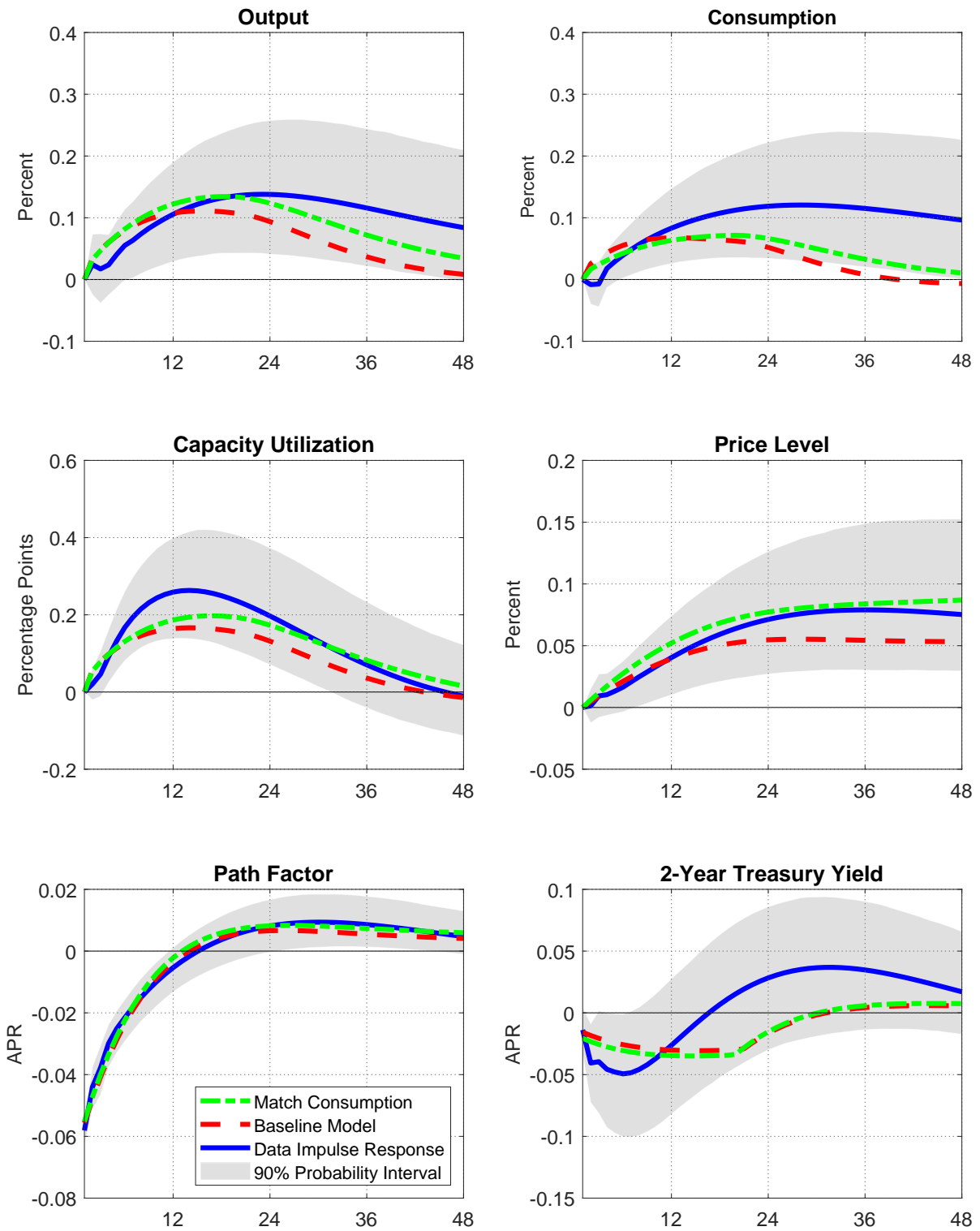
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution. The dashed lines denote model-implied impulse responses.

Figure F.1: Model-Implied Impulse Responses under Tighter Prior for  $\kappa$



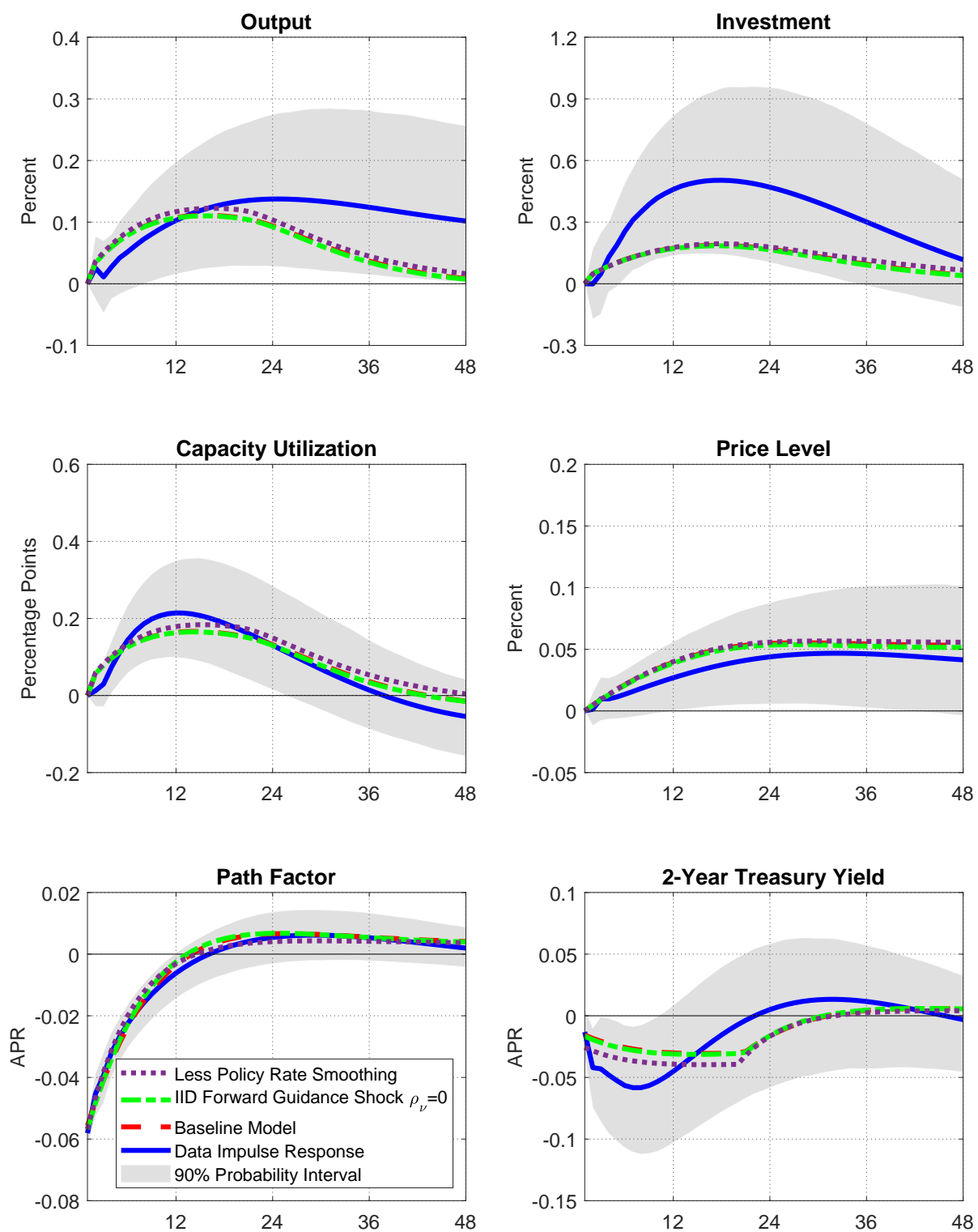
Note: The solid blue line denotes the estimated VAR impulse responses and the shaded region denotes the probability interval of the posterior distribution to a forward guidance shock. The dashed lines denote model-implied impulse responses from either our baseline specification or a specification which uses a tighter prior on the investment adjustment cost parameter  $\kappa$ .

Figure F.2: Empirical & Model-Implied Impulse Responses Using Consumption



Note: The solid blue line denotes the estimated VAR impulse responses and the shaded region denotes the probability interval of the posterior distribution to a forward guidance shock when we replace investment with consumption. The dashed lines denote model-implied impulse responses from either our baseline specification or a re-estimated model which uses consumptions in place of investment.

Figure G.1: Empirical & Model Impulse Responses For Varying Degrees of Rate Persistence



Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution. The dashed lines denote model-implied impulse responses.